Echocardiographic Image Classification Using Deep Learning

Salvador Gomes Neto[1], Samuel Armbrust Freitas[1], Gabriel de Oliveira Ramos[1]

Graduate Program in Applied Computing
Universidade do Vale do Rio do Sinos
São Leopoldo, RS, Brazil
{netosalvador@edu.,samuelaf@edu.,gdoramos@}unisinos.br

Abstract. Left ventricular ejection fraction is a physiological measure obtained by evaluating the cardiac phases of systole or diastole. This parameter represents the contractile capacity of the cardiac ventricular chambers, which several methods can measure, echocardiography being the most cost-effective. The correct ejection fraction assessment is critical for diagnosing and treating most cardiovascular diseases. Although using deep learning to estimate the ejection fraction significantly improves the method's accuracy, there are still difficulties with its extensive application for several reasons. This paper proposes a deep learning pipeline for classifying echocardiographic images in systole or diastole, comparing its performance to the state-of-the-art. The proposed pipeline features a set of pre-processing methods suitable to echocardiographic images and a convolutional neural network tuned for the considered classification task. We also introduce a novel dataset of echocardiographic images without excessive pre-selection of images, thus presenting real-life conditions. We performed several experiments to assess the performance of our approach, through which it was possible to obtain an accuracy of 97.69% and a cross-entropy loss of 0.1883. Our convolutional neural network was able to classify systolic and diastolic images with accuracy similar to the benchmark in the literature. The proposed pipelines present pre-processing methods suitable for echocardiographic images, a convolutional neural network adjusted for the considered classification. However, our network is simpler than the reference, and the dataset is closer to real-life conditions, avoiding excessive pre-selection of images.

Keywords: Deep Learning · Echocardiography · Systole · Diastole · Convolutional Neural Network · Image Classification.

1 Introduction

Left ventricular ejection fraction is a physiological parameter defined as the percentage of blood in the left ventricle in late diastole ejected into the aortic artery. It compares how much blood the left ventricle retains at the beginning of a beat with how much blood remains after the ventricle completes the beat. The ejection fraction ultimately represents the contractile capacity of the cardiac ventricular chambers. This parameter is the most critical information in evaluating the cardiac contractile function [5]. Therefore, correctly evaluating this parameter is the cornerstone for diagnosing and treating almost every cardiac disease.

In cardiology, there are several ways to measure left ventricular ejection fraction. First, we can measure it during cardiac catheterization, an exam used to evaluate the coronary arteries and which also allows analyzing the quality of cardiac contraction. Second, myocardial scintigraphy, where a radiotracer is injected into the patient to check if the blood is circulating properly in the heart's walls. Another approach includes echocardiography, which uses ultrasound waves to allow the visualization of the movement of the structures of the heart and blood flow. Last, ejection fraction can also be measured using nuclear magnetic resonance, which captures images of the heart by applying a magnetic field. Magnetic resonance imaging (MRI) is currently considered the gold standard for assessing ejection fraction.

According to [5], echocardiography is undoubtedly the most cost-effective evaluation method. Unlike other exam options, echocardiography has the best mobility and equipment availability due to its lower acquisition cost and physical dimensions, much smaller than cardiac catheterization, MRI, and scintigraphy. Echocardiography also does not need to expose the patient to the risk of ionizing radiation, nor does it have the issue of claustrophobia, often seen in MRI scans.

Classically, the Swedish physician Helmut Hertz is considered the pioneer of cardiac ultrasound, with his prototypes completed in 1953 [15]. Since then, cardiac ultrasound has been constantly updated, with the addition of numerous improvements in acquisition and image quality obtained over the decades. This evolution and versatility of echocardiography created the need for increasingly in-depth theoretical and practical training for cardiac ultrasonographers. In addition, the complexity of handling left ventricular ejection fraction measurement software brought the need for specific training to handle the equipment.

This complexity causes reasonable intra- and inter-observer variability due to the learning curve required to master the handling technique and the difference in expertise between examiners, impacting the accuracy of echocardiographic exams. This context, besides the monopoly of a few companies in producing analysis software, all with closed source and different reference values, methodologies, and learning curves, further increases the difficulty in training and using the method. That said, the main focus of this proposal is to seek a deep learning model for image classification, annotation, and segmentation, with a performance at least comparable to the gold standard in the literature.

Integrating echocardiography and machine learning is not a new topic, with attempts to use Fourier analysis to evaluate the waveform of mitral leaflets described as far back as 1978 [3]. Even before the deep learning wave [1], many machine learning algorithms had already been applied to assessing cardiac function, image optimization, and structural observation of the heart, including algorithms for contouring the inner walls of the left ventricle in two-dimensional and three-dimensional analyzes [10].

The development of new technologies, such as deep learning and neural networks, has effectively improved the effectiveness of echocardiography [4]. However, even with the growing interest in the role of AI in echocardiography, there are still concerns [2]. One of the main concerns is the need for more standardization of echocardiography, with significant variation in reference values for anatomy and cardiac function parameters. Another critical concern relates to the low robustness of existing methods due to the still insufficient volume of studies of deep learning in the area and vague generalization of the models in clinical applications, which results from the excessive specificity of the parameters used in the studies, with over-selected patients [7], who sometimes end up not representing the actual world pattern [8].

Litjens et al. [6] attempted to summarize the state-of-the-art use of deep learning in cardiology, analyzing more than eighty articles on several diagnostic tests used to assess the heart, with about twenty of them evaluating cardiac ultrasound. That review showed several deep learning algorithms with good results in image classification and assessment of ventricular ejection fraction, but it also raised some unanswered questions. For example, many algorithms are still in the initial research phase, far removed from the clinical standard of exams, allowing us to question their applicability in the real world. In addition, the vast majority of studies were conducted in single diagnostic centers, with a limited sample size, which raises doubts about their generalizability.

Answering these questions would help democratize cardiological care by promoting superior speed and accuracy compared to standard methods. It would also enable the analysis of echocardiographic images obtained with more straightforward equipment and from geographic regions with limited specialized expertise. These gains would reduce assessments' subjectivity and provide a leap of quality in diagnostic performance.

This paper proposes a deep learning approach to classify static, two-dimensional echocardiographic images of the left ventricle as belonging to the systole or diastole phases. To this end, we created a novel dataset based on 54 complete transthoracic cardiac ultrasound scans, yielding 216 images. We then created a new pipeline featuring a set of pre-processing methods to crop and normalize the images and a convolutional neural network to classify the images as belonging to one of the abovementioned classes. We assessed our pipeline's effectiveness through several experiments, in which our method has shown to obtain a 97.69% accuracy. Our accuracy results were similar to those of other approaches in the literature [6]. Nonetheless, our approach presents a more straightforward design. Furthermore, our approach was trained with images more similar to those obtained in everyday ultrasound laboratories without the excessive pre-selection of images commonly found in works in the area.

The main contributions of this work can be summarized as follows:

- A novel dataset of static, two-dimensional echocardiographic images of the left ventricle. The dataset was curated and labeled by a specialist. However, no excessive pre-selection of images was performed, thus rendering the dataset closer to real-world conditions.
- A deep learning pipeline for classifying echocardiographic images as belonging to the systole or diastole phases. The pipeline builds upon a convolutional

neural network, which yields an accuracy similar to or superior to the state-of-the-art methods while making fewer assumptions.
– A building block towards a deep learning pipeline for automatically estimating left ventricular ejection fraction from echocardiographic examinations. Solving the classification task proposed in this work represents a first step in that direction.

The rest of this paper is organized as follows. Section 2 presents a literature overview related this work. Section 3 describes our approach and data collection. Section 4 provides an experimental analysis of our approach. Finally, Section 5 presents the concluding remarks.

2 Related Work

This section overviews relevant works on artificial intelligence approaches for echocardiography-based ejection fraction estimation tasks. Our main objective is to describe our literature review process, seeking to understand the state of the art in the field, the integration between computing science and cardiology, and to identify gaps and research challenges to corroborate our research objective and pointing future research. We set the temporal cut-off point at five years, aiming for the inclusion of current and relevant papers. We perform the article searching in the digital databases Science Direct, IEEE, PubMed, Scielo, Google Scholar, and BMV, as well as events proceedings in Cardiology and Computing. The choice for these digital databases was due to the repositories' relevance and representativeness in the research area. We searched for relevant studies in the area using a string of the following terms: "artificial intelligence" OR "ejection fraction" OR "echocardiography" OR "deep learning" OR "cardiac imaging" OR "cardiology database" OR "ultrasound" OR "left ventricle" OR "global longitudinal strain". The final filtering resulted in twelve papers, considered a basis for the report. The selected papers include review papers, reference articles for data banks in cardiology and echocardiography, comparisons of deep learning methods on different diagnostic modalities, and articles about using artificial intelligence in echocardiographic imaging. As an exception, we include an original article that, although it did not describe the pipeline or make available the neural network source code used, was kept in the final collection because it addresses a new portable device that has received much attention from the cardiology community.

We formulated some questions to guide the critical review of our articles, seeking a minimum standard of evaluation that would allow systematically extracting details from each article and identifying its possible limitations. The questions are presented in Table 1.

In the next paragraphs, critical reviews of some of these evaluated articles are presented.

Assessment and validation of a novel fast fully automated artificial intelligence left ventricular ejection fraction quantification software [13]. The article is a original prospective study. Compares LVivoEF by DIA (a multi-platform

Table 1. Research questions.

Identifier	Question
Q1	What is the study design?
Q2	What deep learning technique was used?
Q3	What are the metrics evaluated?
Q4	What are the main limitations of the study?

software) against cardiac Magnetic Resonance, using deep learning and machine learning. The metrics evaluated weres ensitivity, specificity and accuracy. The study main limitations are the unavailability for a benchmark comparison (closed-source software), the use of DICOM format, not always available, and the large intra-cardiac masses or large stable pericardial effusions, wich proved challenging for the AI program.

Artificial Intelligence applied to support medical decisions for the automatic analysis of echocardiogram images: A Systematic Review [14]. The study design is a systematic review, using convolutional neural networks (CNN), Adaboost, CNN U-NET, Support Vector Machine and Bayes. The metric evaluated was accuracy. The main limitations are the lack of large public datasets and the fact that the models are too sensitive to noisy images.

Fully Automated Echocardiogram Interpretation in Clinical Practice [16]. The article is an original, prospective article, using CNN as the deep learning technique. The metric evaluated was accuracy. The main limitation is, despite the enormous number of examinations, the proposed methods are not suitable for independent use in a clinical setting.

Use of artificial intelligence for real-time automatic quantification of left ventricular ejection fraction by a novel handheld ultrasound device [11].This work is a original prospective study. Compares his automatic ejection fraction method with Kosmos HUV® for point-of-care echocardiography with the manual biplane Simpson´s method, resulting in a correlation coefficient r = 0.87. The deep learning technique is the image segmentation. The metrics are correlation and accuracy. The main limitations are the unavailability of the code for a benchmark comparison (closed-source software), besides the fact the study compares the automatic ejection fraction software performance in a small dataset (only 100 patients).

Deep learning/artificial intelligence for automatic measurement of global longitudinal strain by echocardiography [12]. The work is a original prospective study. Compares conventional LV Global Longitudinal Strain against the vendor-specific software (EchoPAC, GE Healthcare). The study uses deep learning, evaluating the metrics through Bland-Altman analysis. The main limitations are the unavailability of the code for a benchmark comparison (closed-source software), and the comparison of the automatic Global Longitudinal Strain software in a small dataset (only 100 patients). besides this, the viability of the manual method was greater than that of the automated one, with the software requiring specific training with a long learning curve.

Real-Time Standard View Classification in Transthoracic Echocardiography using Convolutional Neural Networks [9]. It is a original study. The researchers developed a CNN for cardiac view classification, using the AlexNet architecture, Inception architecture, or the network proposed by the authors, cardiac view classification architecture, with an accuracy of 98,3%; The deep learning technique was CNN, and the metric evaluated was accuracy. That was our benchmark study. They use a neural network more complex than ours. The model had some difficulties regarding poor images.

The heterogeneity of the studies is quite clear. In many works, the code used to build the network was unavailable, and the pipelines needed to be clarified. Some models were too sensitive to noise. In practically all of them, interobserver variability was highlighted. This variability is due, among other causes, to the significant heterogeneity of expertise among the exam executors, due to the generally long learning curve. In addition, many works focused on validating new equipment grouped by major players, which keeps the datasets for comparison and the source code of the analysis algorithms unavailable. Many works focused on validating new equipment grouped by major players, which keeps the datasets for comparison and the source code of the analysis algorithms unavailable. Another critical point is the excessive pre-selection of the data, often taking the dataset out of the real-world context and making it difficult to apply the methods in complex or unfavorable cases. This facts uncovered a significant challenge: the urge for agnostic, multi-platform interpretation algorithms. Our research questions address precisely this gap. In this work, we overcome the interobserver variability with only one experienced cardiologist performing all the ecocardiographic examinations of the study. Moreover, we are not making pre-selection of the data, nor excluding the patients with suboptimal echocardiographic window, to approach our dataset to the reality of a standard cardiac clinic. Lastly, we are setting our ultrasound device with a simple preset configuration, easily reproducible in any commercially available ultrasound equipment.

3 Proposed Method

In this section, we introduce a deep learning pipeline for classifying images of the systole and diastole of the left ventricle. We trained and tested our pipeline using a novel dataset of images extracted from cardiac ultrasound exams performed in two cardiology diagnostic centers. Our pipeline aims to help the left ventricular ejection fraction estimation task by automatically identifying whether a cardiac image represents the systole or diastole phase. Our approach is a building block to enable the automation of ejection fraction exams. It is always imperative to highlight how much the automation of ejection fraction estimation reduces interobserver variability, increases the reproducibility of results, and reduces the time spent performing echocardiographic exams.

3.1 Data collection

We collected the dataset from 54 complete transthoracic cardiac ultrasound scans performed by a cardiologist with experience in cardiac imaging at two cardiology diagnostic clinics in Parobé and Porto Alegre, RS, Brazil. We used a Phillips CX50 ultrasound scanner (Koninklijke Philips N.V.) with a multifrequency sectoral transducer. We set the transducer emission frequency at 2MHz and the PRF (pulse repetition frequency) at 40fps (frames per second), with penetration depth between 10 and 15 centimeters, and the focal zone optimized for each patient, according to the biotype and the quality of the echocardiographic window. We captured the electrocardiographic tracing simultaneously with the ultrasound examination in all patients. From the apical four-chamber echocardiographic window, we selected static frames of diastole and ventricular systole in two consecutive cardiac cycles (beats). We used the electrocardiogram tracing, the position of the mitral valve (open in diastole and closed in systole), as showed in Fig. 1, and the subjective evaluation of the edges of the ventricle to choose the best frame for the record. We obtained four images for each patient (two systolic and two diastolic images), totaling 108 systolic and 108 diastolic images, 216 in total.

3.2 Data Preparation

We extract the images in BMP (Bitmap Image File) format, with 800x600 pixels, and convert them to PNG (Portable Network Graphics) format for greater compression. Next, we cropped the images from the borders (198 pixels from the left border, 64 pixels from the top border, 110 pixels from the right border, and 8 pixels from the bottom border), reducing them to 492x455 pixels, as shown in Fig. 2. The cropping was necessary to hide patient identification and exclude electrocardiographic tracing from the image, which could cause some bias during neural network training. We then grouped the cropped images into systole and diastole, with 108 images in each group.

Figure 1 shows two examples of pre-crop images, in diastole (left) and in systole (right), highlighting in the center of the images the mitral valve in its moment of maximum opening, in ventricular diastole and its moment of closure, in systole. The image displays the electrocardiogram tracing in green at the bottom of the image. The vertical line on the tracing shows the time phase corresponding to the moment of the cardiac cycle (systole or diastole). We chose to crop the electrocardiographic tracing precisely to force the neural network to classify the image focusing on the ventricle and the position of the mitral valve.

Figure 2 presents the same images as in Fig. 1 after the cropping process, omitting the patient's identification and the electrocardiographic tracing, focusing on the sectorial image of the heart.

3.3 Neural network architecture

We develop a convolutional neural network using Python and TensorFlow in this work. First, we create our network as a sequential model with five convolution

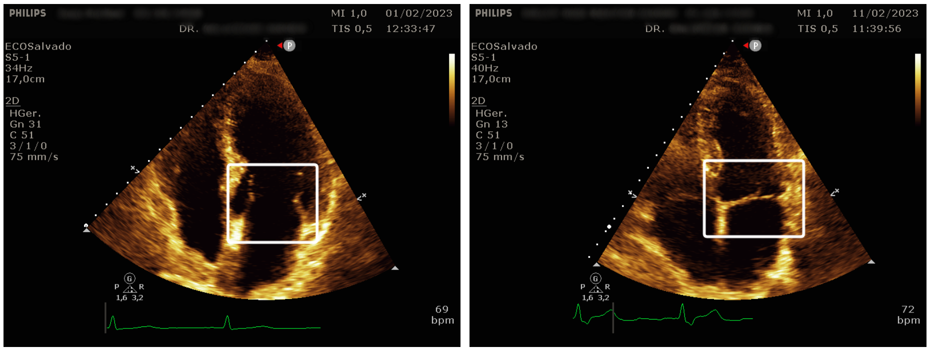

Fig. 1. Example of static images of the left ventricle in diastole (left) and systole (right). The white box highlights the mitral valve. Patient and examining physician identification were hidden for privacy protection.

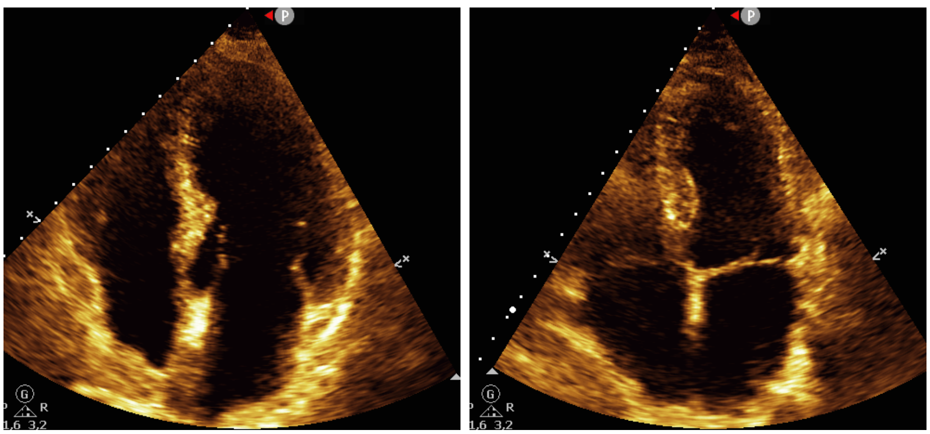

Fig. 2. Cropping of the images from Figure 1.

layers, each with a kernel size of 3. We set the padding to "same" and used the rectified linear unit (ReLU) activation function. The number of units in the convolution layers was set to 16, 32, 64, 128, and 256, respectively. After each convolution layer, we include a dropout layer with 20% to prevent overfitting and a max pooling operation layer for downsampling the input. Then, we create a flattening layer and, in sequence, a densely-connected layer with 128 units and activation filter ReLU. At last, we add a final dropout layer, again with 20% dropout, and a densely-connected layer as output, with 2 units (one per class) and no activation function. The overall architecture of the proposed network is presented in Fig. 3.

For the dataset analysis process, we consider two classes of images, systole and diastole. We grouped the images in batches of 32 images each, with a standardized dimension of 180x180 pixels. We randomly allocated 80% of the images

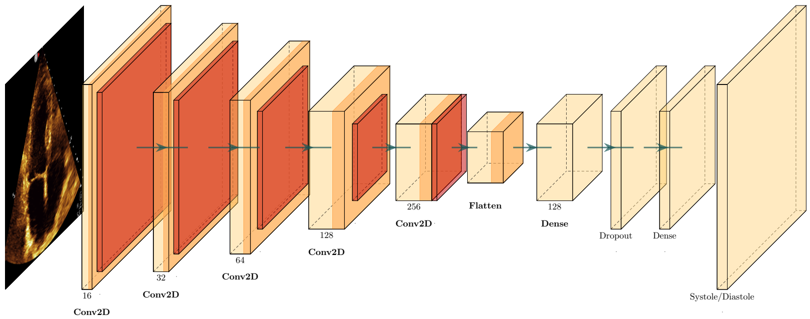

Fig. 3. Architecture of the proposed Convolutional Neural Network for Image Classification.

for training and the remaining 20% for validation. The runtime and prefetch were dynamically adjusted, and the RGB channel values were scaled from $[0, 255]$ to $[0, 1]$. We used the ADAM algorithm as optimizer, with a cross-entropy loss function, and measured accuracy as the evaluation metric.

4 Experimental Evaluation

This section presents an empirical analysis of our approach. In particular, the purpose of the experiments is to assess the performance of our pipeline when it comes to classifying echocardiographic images as representing systole or diastole phases.

4.1 Methodology

We hypothesize that our pipeline can perform the classification of systolic and diastolic images at least similarly to the state-of-the-art study by Ostvik et al. [9] (O19, henceforth). To this end, we employ O19 as a comparison baseline. The hyper-parameters of our pipeline were empirically optimized. The experiments here presented encompass the best such configuration.

In order to assess and compare the performance of the considered approaches, we employed accuracy as the main metric, as this is suitable for balanced data, as is our case. Additionally, we also computed precision, recall, and specificity. The True/False Diastole/Systole countings were also reported. All these metrics were collected compared from ours and the baseline models.

4.2 Numerical results

Table 2 presents the main results of our approach and of O19 for the considered metrics. As seen, our approach achieved a validation accuracy of 97.69% for detecting systole, diastole, and aggregated images, with a validation loss of 0.1883.

Our accuracy was very close to that obtained by O19, whose network obtained 98.3% accuracy per single frame and image sequence, with better performance when classifying groups of images, achieving a precision of 99% and a recall of 99.3%. We obtained a precision rate of 97.25% for diastole images, 98.13% for systole images, and 97.69% for aggregated. Regarding the recall metric, we achieved 98.15% for the diastole images, 97.22% for systole images, and 97.68% for aggregate. Finally, we obtained a specificity of 97.22% for diastole images, 98,15% for systole, and 97.68% in aggregated images.

Table 2. Comparison of the results obtained by our approach and by the O19 [9] baseline. Metrics were collected per class (Diastole and Systole columns) and in a consolidated manner (Aggregated column).

Metric	O19 [9]	Diastole	Systole	Aggregated
Accuracy	0.983	0.9769	0.9769	0.9769
Precision	0.985	0.9725	0.9813	0.9769
Recall	0.985	0.9815	0.9722	0.9768
Specificity	-	0.9722	0.9815	0.9768
True Diastole	-	-	-	106
False Diastole	-	-	-	3
True Systole	-	-	-	105
False Systole	-	-	-	2

Our results allow us to validate the hypothesis that the performance of our convolutional network is similar to that of the considered baseline for the image classification purpose. However, instead of O19, our approach yields such results using a much simpler neural network architecture, further contributing to its adoption in the real world. Another advantage of our approach compared to O19 relates to our novel dataset, which is significantly smaller, having 54 patients and 216 images, in contrast to more than 500 patients and 7000 videos in the O19 dataset. Regarding the number of epochs, our work needed around 200 to 250 to obtain the reported accuracy during the various empirical optimization attempts against 100 epochs in the O19 experiment.

Figure 4 presents the learning curves of our model in terms of accuracy and loss. As can be observed, after approximately 200 epochs there was a tendency for the training trace to stabilize, with some oscillations in the validation curve. Regarding the training and validation loss curve, we see that there is practically no variation in loss over the epochs, undoubtedly due to the low number of samples in the dataset, which turns out to have a relatively homogeneous, facilitating training.

It should be noted that our model misclassified two out of 108 diastolic images and three out of 108 systolic images. By analyzing the images misclassified by the model, it is possible to notice that the definition of the mitral valve and the left ventricle in these images is suboptimal, as seen in Figs. 5 and 6. After we deleted the misclassified images from the dataset, the accuracy increased to as high as

99%. However, in spite of such improvement, we decided to keep the suboptimal images in the dataset precisely to avoid excessive pre-selection and approximate the actual day-to-day conditions of a cardiology diagnostic laboratory.

5 Concluding Remarks

This paper presented a deep learning approach to classify echocardiographic images of the left ventricle as representing systole or diastole images. This work also featured a novel dataset encompassing 216 echocardiographic images belonging

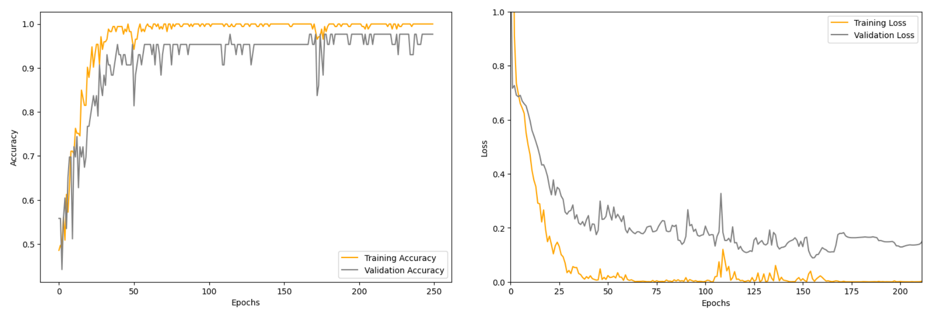

Fig. 4. Learning curves regarding accuracy (left) and loss (right) along epochs.

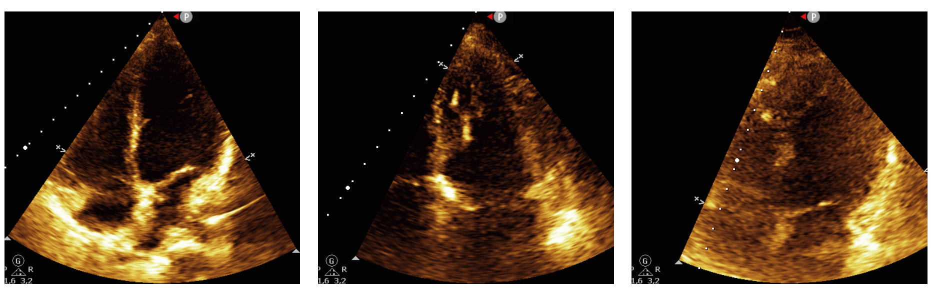

Fig. 5. Misclassified systole images.

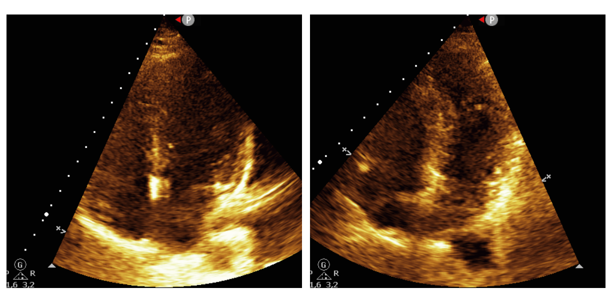

Fig. 6. Misclassified diastole images.

to the two considered classes. We develop a classification model with equivalent performance to the gold standard (accuracy of 0.983 in Ostik et al. versus 0.977 in our network). However, as opposed to previous work, our approach presents a simpler architecture with lower complexity, and was trained on much smaller dataset that better resambles real-world conditions.

We remark that the proposed approach represents an initial step towards a complete deep learning pipeline for automatically estimating left ventricular ejection fraction from echocardiographic examinations. As previously discussed, ejection fraction is a key parameter to assess the cardiac contractile function, which typically relies on expensive exams to be measured. A deep learning pipeline to automate such task thus represents a strategic movement towards democratizing cardiological care and increasing speed and accuracy of these exams. The study's main limitation refers to the relatively small dataset size. Nonetheless, we are still collecting new samples from new patients, which should enable the development of further research. We hope that, with the increase in the dataset, we can better adjust the model towards a greater generalization in image classification. Finally, we firmly insist on avoiding excessive pre-selection of images as an essential condition for the future generalization and expansion of the model. Solving the classification task proposed in this work represents a first step in that direction.

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