Automatic Quantification of Volumes and Biventricular Function in Cardiac Resonance. Validation of a New Artificial Intelligence Approach

Cuantificación automática de los volúmenes y función de ambos ventrículos en resonancia cardíaca. Propuesta y evaluación de un método de inteligencia artificial

ABSTRACT

Background: Artificial intelligence techniques have shown great potential in cardiology, especially in quantifying cardiac biventricular function, volume, mass, and ejection fraction (EF). However, its use in clinical practice is not straightforward due to its poor reproducibility with cases from daily practice, among other reasons.

Objectives: To validate a new artificial intelligence tool in order to quantify the cardiac biventricular function (volume, mass, and EF). To analyze its robustness in the clinical area, and the computational times compared with conventional methods.

Methods: A total of 189 patients were analyzed: 89 from a regional center and 100 from a public center. The method proposes two convolutional networks that include anatomical information of the heart to reduce classification errors.

Results: A high concordance (Pearson coefficient) was observed between manual quantification and the proposed quantification of cardiac function (0.98, 0.92, 0.96 and 0.8 for volumes and biventricular EF) in about 5 seconds per study.

Conclusions: This method quantifies biventricular function and volumes in seconds with an accuracy equivalent to that of a specialist.

Key Words: Deep Learning – Heart Diseases / Diagnostic Imaging – Open Source - Magnetic Resonance Imagin.
it impossible to implement them in clinical practice. Therefore, there is a need to gain an objective understanding of the advantages and weaknesses when applying these techniques in the clinical setting. In this regard, we will analyze the robustness of deep neural networks to quantify cardiac function in terms of volumetric measurement and systolic function for both left and right ventricles in cardiac magnetic resonance imaging (CMRI).

A manual or semi-automatic quantification of the main cardiac structures (atria, ventricles, and myocardial tissue) normally used to diagnose and quantify various conditions such as infarction or hypertrophy, requires an intrinsically subjective, repetitive and laborious task that must be performed by a specialist. (6) This analysis takes 3-10 minutes per study, depending on the specialist’s expertise. (7) Today, there are several applications for semi-automatic quantification, (8-10) but in clinical practice, detecting chambers and myocardial tissue is deficient. Most often, it involves manual intervention by a specialist, which is time-consuming. Therefore, the development of accurate, robust and subjectivity-free techniques continues to be an active area of research. In this respect, AI techniques seem to be the right tools to overcome these limitations and reduce quantification times to seconds.

This paper introduces a new AI application based on deep neural networks to automatically quantify cardiac function from the estimation of left and right ventricles and myocardial tissue in CMRI. Firstly, we have analyzed its robustness with multicenter data, with special emphasis on the effects and benefits observed when adjusting the application to CMRI of a medical center; and secondly, we have compared the time required by this method against the traditional manual method.

**METHODS**

A retrospective, observational study was conducted in 89 patients (51 ± 17 years, 67% men) with several conditions (left bundle branch block, acute myocardial infarction, dilated cardiomyopathy, hypertrophic cardiomyopathy, hypertensive cardiomyopathy), and normal cardiac function, from a health center in Bariloche (SSC). Images were obtained over a 2-year period with a Philips Intera 1.5T scanner. Chamber segmentation was performed by a specialist using the Segmentation software, which was also used to estimate the ejection fraction (EF), end-diastolic volume (EDV) and end-systolic volume (ESV) of both ventricles, and the LV myocardial mass.

A publicly available dataset, the Automatic Cardiac Diagnosis Challenge (ACDC) was used to assess the robustness of the proposed technique. (11) The database was made of 100 patients with conditions similar to those described above. Images were acquired over a 6-year period using two Siemens 1.5 and 3T scanners.

**Proposed method**

CardIAc, the proposed application, was developed as an extension of the 3D Slicer software. (12) Figure 1 shows an example of the user interface and quantification for a patient from the SSC. The extension was developed to be used on a common computer, available today in any medical center.

Automatic quantification is performed with two convolutional neural networks (CNN) based on a U-Net architecture. (13) The first CNN is used to identify a region of interest (RoI) that includes the entire heart. This region is defined in 90 mm x 90 mm (~128 x 128 pixels). Once the RoI around the heart is identified, a second neural network estimates the different structures of interest. The second neural network adds information of the anatomical structure of the heart following a variational autoencoder approach. (14) This way, errors in detecting anatomically non-plausible structures are reduced. Finally, biventricular volumes and EF and LV mass are quantified. Furthermore, if the user enters the patient’s height and weight, volumes and mass are normalized using the body mass index.

**Statistical analysis**

Data were collected as mean ± standard deviation, and differences were evaluated using a Student’s t-test or t-test. In addition, the linear correlation between the proposed method and manual quantification was analyzed, and Pearson’s correlation coefficient was calculated. Systematic errors and degree of concordance were assessed with a Bland and Altman analysis.

**Ethical considerations**

The study was conducted in compliance with the National Data Protection Act No. 25 326, protecting patients’ identity and personal data. All sensitive information was anonymized. The study was conducted in accordance with national and regional ethical standards, and its protocol was approved by the Ethics Committee in the province of Río Negro, Argentina.

**RESULTS**

Three sets of experiments were carried out in order to analyze the accuracy and robustness of the proposed method. The aim of the first experiment was to study the accuracy of the proposed techniques using only public ACDC data, both for training and validation (Table 1).

The second experiment analyzed the accuracy of the proposed tool on daily practice data; in this regard, only SSC data provided by the local center were used (Table 2). In both cases, the accuracy of the proposed method was similar to the interobserver error for LVEF reported in the literature (2.7 ± 6.8%), (15) being 0.60 ± 4.77 % and 0.89 ± 4.55 % for ACDC and SSC respectively.

The third experiment studied the accuracy obtained when only a public database is used to train the proposed models (Table 3). It is important to note that the proposed tool was suitable to quantify the variables analyzed (Tables 1 and 2). However, when analyzing the robustness of the techniques on the data from the regional center, the accuracy decreases substantially compared to the results obtained when the proposed technique was trained on the regional SSC data. In particular, the error obtained when esti-
**Fig. 1.** Example of the proposed AI-based application within the 3D Slicer software

**Table 1.** Quantification of study variables for ACDC data (training and validation)

|                  | Manual         | AI             | p   | r    | Bland-Altman |
|------------------|----------------|----------------|-----|------|--------------|
| LV EDV [mL]      | 164.61 ± 73.90 | 162.22 ± 70.93 | 0.01| 0.99 | -2.39 (-20.08 a 15.29) |
| LV ESV [mL]      | 99.06 ± 78.36  | 98.09 ± 75.74  | 0.314| 0.99 | -0.97 (-19.07 a 17.76)  |
| RV EDV [mL]      | 152.99 ± 54.88 | 151.07 ± 54.15 | 0.142| 0.97 | -1.92 (-27.20 a 23.36) |
| RV ESV [mL]      | 85.88 ± 52.20  | 88.81 ± 55.52  | 0.091| 0.95 | 2.92 (-30.50 a 36.35)  |
| LVEF [%]         | 46.38 ± 19.82  | 45.79 ± 19.69  | 0.217| 0.97 | -0.60 (-9.94 a 8.75)  |
| RVEF [%]         | 46.73 ± 17.80  | 44.69 ± 17.89  | 0.018| 0.89 | -2.04 (-18.60 a 14.52) |
| LV Mass [g]      | 129.96 ± 50.75 | 129.36 ± 49.96 | 0.441| 0.99 | -0.60 (-15.85 a 14.64) |

LV: Left ventricle. RV: Right ventricle. EDV: End-diastolic volume. ESV: End-systolic volume. EF: Ejection fraction. AI: Artificial intelligence.

**Table 2.** Quantification of study variables for SSC data (training and validation)

|                  | Manual         | AI             | p   | r    | Bland-Altman |
|------------------|----------------|----------------|-----|------|--------------|
| LV EDV [mL]      | 166.97 ± 44.74 | 164.50 ± 41.87 | 0.05| 0.98 | -1.65 (-15.56 a 12.26) |
| LV ESV [mL]      | 74.32 ± 44.48  | 74.54 ± 43.70  | 0.83| 0.98 | -0.13 (-11.73 a 11.98) |
| RV EDV [mL]      | 149.80 ± 33.06 | 143.40 ± 35.03 | 0.002| 0.92 | -6.41 (-43.17 a 19.61) |
| RV ESV [mL]      | 61.89 ± 20.55  | 64.71 ± 22.45  | 0.003| 0.95 | 2.82 (-13.96 a 19.61) |
| LVEF [%]         | 58.02 ± 12.16  | 57.13 ± 15.31  | 0.07| 0.96 | -0.89 (-9.82 a 8.04)  |
| RVEF [%]         | 59 ± 8.61      | 54.38 ± 14.45  | < 0.001| 0.8 | -4.63 (-22.48 a 13.22) |
| LV Mass [g]      | 141.11 ± 36.72 | 142.84 ± 35.08 | 0.21| 0.97 | -1.14 (-12.32 a 14.59) |

LV: Left ventricle. RV: Right ventricle. EDV: End-diastolic volume. ESV: End-systolic volume. EF: Ejection fraction. AI: Artificial intelligence.
Table 3. Quantification of study variables for SSC data using ACDC (ACDC Training) and SSC (SSC Training) data as training

| LV EDV [mml] | LV ESV [mml] | RV EDV [mml] | RV ESV [mml] | LV EF [%] | RVEF [%] | LV Mass [g] |
|--------------|--------------|--------------|--------------|-----------|---------|------------|
| Manual       | AI           | f            | AI           | SSC Training | r        |
| 166.97 ± 44.74 | 150.46 ± 38.52 | 0.98         | 164.50 ± 41.87 | 0.98 |
| 74.32 ± 44.48 | 73.35 ± 39.97 | 0.98         | 74.54 ± 43.70 | 0.98 |
| 149.80 ± 33.06 | 129.95 ± 35.98 | 0.92         | 143.40 ± 35.03 | 0.92 |
| 61.89 ± 20.55 | 69.35 ± 32.81 | 0.95         | 64.71 ± 22.45 | 0.95 |
| 58.02 ± 12.16 | 51.75 ± 20.94 | 0.96         | 57.13 ± 15.31 | 0.96 |
| 59 ± 8.61      | 46.76 ± 19.22 | 0.8          | 54.38 ± 14.45 | 0.8 |
| 141.11 ± 36.72 | 106.10 ± 30.17 | 0.97         | 142.84 ± 35.08 | 0.97 |

LV: Left ventricle. RV: Right ventricle. EDV: End-diastolic volume. ESV: End-systolic volume. EF: Ejection fraction. AI: Artificial intelligence.

CONCLUSIONS
To the best of our knowledge, ours is the first study in Argentina to introduce a user-friendly tool to quantify cardiac function using AI techniques, which in turn, can be adapted to the needs of different national centers to obtain accurate quantification in a few seconds and in real-world cases.

Conflicts of interest
None declared.

(See authors’ conflict of interests forms on the web/Additional material.)

REFERENCES
1. Baskaran L, Malaikal G, Al’Aref S, Singh G, Xu Z, Michalak K, et al. Identification and quantification of cardiovascular structures from CCTA: An End-to-End, Rapid, Pixel-Wise, Deep-Learning Method. JACC Cardiovascular Imaging 2020;13:1163-71. https://doi.org/10.1016/j.jcmg.2019.08.025.
2. Kawel-Bohm N, Hetzel SJ, Ambale-Venkatesh B, Captur G, Francois CJ, Jerosch-Herold M. Reference ranges (“normal values”) for cardiovascular magnetic resonance (CMR) in adults and children: 2020 update. J Cardiovasc Magn Reson 2020;22:87. doi:10.1186/s12968-020-00683-3.
3. Curiale AH, Colavecchia FD, Mato G. Automatic quantification of the LV function and mass: A deep learning approach for cardiovascular MRI. Comput Methods Programs Biomed 2019;169:37-50. https://doi.org/10.1016/j.cmpb.2018.12.002.
4. Dey D, Slomka PJ, Leeson P, Comaniciu D, Shrestha S, Sengupta PP, et al. Artificial intelligence in cardiovascular imaging. J Am Coll Cardiol 2019;73:1317-35. doi:10.1016/j.jacc.2018.12.054.
5. Zheng Q, Delingette H, Duchateau N, Ayache N. 3-D Consistent and Robust Segmentation of Cardiac Images by Deep Learning With Spatial Propagation. IEEE Trans Med Imaging 2018;37:2137-48. https://doi.org/10.1109/TMI.2018.2820742.
6. Rosado-Toro JA, Abidov A, Altbach MI, Oliva IB, Rodrigues JJ, Avery RD. Segmentation of the right ventricle in four chamber cine cardiac MR images using polar dynamic programming. Comput Med Imaging Graph 2017;62:15-25 https://doi.org/10.1016/j.compmedimag.2017.08.002.
7. Graça B, Donato P, Ferreira MJ, Castelo-Branco M, Caseiro-Alves F. Left ventricular diastolic function in type 2 diabetes mellitus and the association with coronary artery calcium score: a cardiac MRI study, Am J Roentgenol 2014;202:1207-14. https://doi.org/10.2214/AJR.13.11325.
8. Litjens G, Kooi T, Bejnordi BE, Setio AA, Ciompi F, Ghafoorian M. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60-88. doi:10.1016/j.media.2017.07.005.

Limitations
The proposed tool needs refinement for proper determination of RV volumes, as the RV structure is more complex than that of the LV. Further multicenter studies are required to increase and validate the accuracy of the application, particularly in centers with different equipments and patients with different heart conditions.
9. Kim YC, Kim KR, Choe YH. Automatic myocardial segmentation in dynamic contrast enhanced perfusion MRI using Monte Carlo dropout in an encoder-decoder convolutional neural network. Comput Methods Programs Biomed 2020 Mar;185:105150. doi:10.1016/j.cmpb.2019.105150.

10. Larrazabal AJ, Martínez C, Glocker B, Ferrante E. Post-DAE: Anatomically Plausible Segmentation via Post-Processing With Denoising Autoencoders. IEEE Trans Med Imaging 2020;39:3813-20. https://doi.org/10.1109/TMI.2020.3006297.

11. Bernard O, Lalande A, Zotti C, Cervenansky F, Yang X, Heng PA, et al. Deep Learning Techniques for Automatic MRI Cardiac Multi-Structures Segmentation and Diagnosis: Is the Problem Solved? IEEE Trans Med Imaging 2018;37:2514-25. https://doi.org/10.1109/TMI.2018.2837502.

12. Fedorov A, Beichel R, Kalpathy-Cramer J, Finet J, Fillion-Robin J-C, Pujol S, et al. 3D Slicer as an image computing platform for the Quantitative Imaging Network. Magn Reson Imaging 2012;30:1323-41. https://doi.org/10.1016/j.mri.2012.05.001.

13. Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation. In: Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Navab N, Hornegger J, Wells WM and Frangi AF, eds, 2015 pp. 234-241. https://doi.org/10.1007/978-3-319-24574-4_28.

14. Kingma DP, Welling M. Auto-encoding variational Bayes. arXiv preprint arXiv:1312.6114, 2013.

15. Suinesiaputra A, Sanghvi MM, Aung N, Paiva JM, Zemrak F, Fung K, et al. Fully-automated left ventricular mass and volume MRI analysis in the UK Biobank population cohort: evaluation of initial results. Int J Cardiovasc Imaging 2018;34:281-91. https://doi.org/10.1007/s10554-017-1225-9.