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Estimating Ejection Fraction from a new dataset via Deep-Learning using EchoNet-Dynamic library: A preliminary study

Estimando la Fracción de Eyección a partir de un nuevo conjunto de datos con Aprendizaje Profundo usando la biblioteca EchoNet-Dynamic: Estudio Preliminar

Alberto Hurtado Armas[1], Alberto Taboada-Crispi[1], Arian Nodarse Concepción[2], Juan Adolfo Prohias Martínez[3], Roberto Diaz-Amador[4]

1- Universidad Central "Marta Abreu" de Las Villas, Cuba. E-mail: aharmas@uclv.cu, ataboada@uclv.edu.cu

2- Cardiocentro "Ernesto Che Guevara", Cuba. E-mail: nodari@gmail.com

3- Cardiocentro del Hospital Clínico-Quirúrgico "Hermanos Ameijeiras", Cuba. E-mail: prohias@infomed.sld.cu

4- Universidad Católica del Maule, Chile. E-mail: rodiaz@ucm.cl

Abstract: Problem to deal with. More than 64 million people worldwide are affected by heart failure syndrome. In this context, the early diagnosis is vital to provide an adequate and effective treatment. Ejection fraction estimation from echocardiograms is one of the main parameters for the diagnosis, but it is difficult to achieve manually. **Aims.** To explore recent Deep-Learning-based algorithms to estimate the ejection fraction automatically or semiautomatically. **Methodology.** We present an application of a Deep Learning model to estimate the ejection fraction using the EchoNet-Dynamic library with a new dataset acquired in Cuba. **Results and Discussion.** A quantitative analysis shows a Mean Absolute Error of 8.96% and a Pearson Correlation of 0.52. Finally, we present a discussion based on Bland-Altman plot. **Conclusions.** Although results are modest, this research paves the way to increase the use of artificial intelligence as a complement in clinical diagnosis for heart failure syndrome.

Resumen: Problema a tratar. *Más de 64 millones de personas en todo el mundo están afectadas por el síndrome de insuficiencia cardiaca. En este contexto, el diagnóstico precoz es vital para proporcionar un tratamiento adecuado y eficaz. La estimación de la fracción de eyección a partir de ecocardiogramas es uno de los principales parámetros para el diagnóstico, pero es difícil de conseguir manualmente.* ***Objetivos.*** *Explorar algoritmos recientes basados en Aprendizaje Profundo para estimar la fracción de eyección de forma automática o semiautomática.* ***Metodología.*** *Presentamos una aplicación de un modelo de Aprendizaje Profundo para estimar la fracción de eyección utilizando la biblioteca EchoNet-Dynamic con un nuevo conjunto de datos adquiridos en Cuba.* ***Resultados y Discusión.*** *Un análisis cuantitativo muestra un Error Absoluto Medio de 8,96 y una Correlación de Pearson de 0,52. Finalmente, presentamos una discusión basada en el gráfico de Bland-Altman.* ***Conclusiones.*** *Aunque los resultados son modestos, esta investigación abre el camino para incrementar el uso de la inteligencia artificial como complemento en el diagnóstico clínico del síndrome de insuficiencia cardiaca.*

Keyswords: Ejection fraction; Deep learning; Heart failure syndrome; Bland-Altman plot

Palabras Claves: *Fracción de eyección; Aprendizaje profundo; Síndrome de insuficiencia cardiaca; Gráfica de Bland-Altman.*

1. Introduction

Recent studies show that heart failure syndrome (HF) affects more than 64 million people worldwide [1]. The early diagnosis of HF can provide that the treatment may be easier and more effective, and medical appointments can be short. The diagnosis includes, as a very important aspect, the estimation of the ejection fraction (EF). The EF is the amount of blood, expressed in percentage, that is pumped out of a filled ventricle with each heartbeat. The risk of HF is usually related with left ventricular EF [2]. Regarding the ejection fraction, HF can be with preserved ejection fraction [3] or with reduced ejection fraction [4].

The calculation of the ejection fraction is usually performed from the 2D echocardiogram using manually the Simpson's Method [5]. The Simpson's method is considered the gold standard for this calculation [6]. Early, with the increases of echocardiogram studies, storage capacity and computer processing, research is focusing on the use of Artificial Intelligence (AI) and Deep Learning techniques to detect HF [7], [8]. Some studies in this direction are reported in [9]–[11]. In [9] the authors present three different convolutional architectures to assess the ejection fraction using EchoNet Dynamic. In [10], the authors present a new method based on EchoNet Dynamic for beat to beat assessment of cardiac function. Finally, in [11], authors report a cyclical semi-supervised approach for EF prediction based on the fact that the heartbeat is a cyclical process with temporal repetition. All of these methods report a mean absolute error (MAE) less than 4.17. In the current work, we propose the use of EchoNet-Dynamic library to estimate the EF in a new dataset. The results are useful to validate the deep learning approach in EF estimation.

2. Methodology

A public available dataset, provided by Stanford University, consists of 10030 videos of patients undergoing 4-chamber echocardiography [9]. From them, 7465 were used to train the DL model. In all cases, subsamples images of dimensions 112 x 112 pixels are generated. The echocardiograms were obtained from ultrasonic devices Epic1C, iEE33, CX50, Epig5G, and from some other devices in different hospital centers. The dataset contains the EF estimated by medical experts using Simpson's method.

On the other hand, the testing data were obtained from 19 patients with an Aloka alfa 10 and a Philips Epic 7 echocardiographs in the Cardio center hospital "Ernesto Guevara", in Santa Clara, Cuba. All cases were evaluated by a team of specialist and the EF was calculated by the Simpson's method, which will be used as gold-standard.

Echonet-Dynamic is a free library written in Python that uses Depp learning models to process and measure parameters from 4-chamber echocardiogram videos. The pipeline allows preprocessing, to segment and to train new DL models with a different dataset (a proprietary one) or to use pre-trained models with the Stanford dataset previously described. In this work, we use the pre-trained DL model **r2plus1d_18** to compute the EF in a new data set, which comprise 19 new cases. The Echonet-Dynamic model include a semantic segmentation of the left ventricle and spatial and temporal 1D and 2D convolution. The input is the video data frame of each of the cases, and the output is the estimated EF. The main coding and scripts are available at [12].

In this work, we use the Mean Absolute Error (MAE), which is calculated by taking the absolute value of the differences between measurements and then computing the average of them, as in equation (1).

$$MAE = \frac{\sum_{n=1}^{N} x_{o_n} - x_{c_n}}{N}, \quad (1)$$

where x_{o_n} and x_{c_n} are the observed and computed values in the n-th position, and N is the total number of cases. Also, we computed the Pearson Correlation between EF observed and EF estimated.

Finally, we discuss the results using a Bland-Altman plot. In the Bland-Altman plot, the Y axis shows the differences between the gold-standard and the EF computed by EchoNet Dynamic, while the X axis shows the differences of EF computed with respect to the gold-standard.

3. Results and Discussion

Table 1 shows the results of EF obtained from the dataset, where we can show the differences between observed and computed values and the computed MAE.

The observed EF mean is 56.24%, with a standard deviation of 12.18%, and median of 60.8%. It implies that most of the cases shows EF in the range considered normal or healthy (50% ≤ EF ≤ 70%). Although it does not necessarily implies a problem in the algorithm to compute EF, it is important to take into account in the results interpretation. The table 1 shows clearly that the EF MAE increases with respect to results previously reported in [9]–[11]. Moreover, the Pearson Correlation between train and test show a moderate 0.51 that indicate a weak correlation. The causes of theses inconspicuous results can be related with to two facts. Firstly, the acquisition protocol, devices and construction of the gold standard are different in both train and test datasets. In addition, the reduced number of cases for test limited the statistical analysis. However, preliminary results show that DL is a promising tool for EF estimation in echocardiography.

Table 1: Results of EF estimated by the model.

Case	EF Observe (%)	EF Computed (%)	Case	EF Observe (%)	EF Computed (%)
Case 1	55.00	57.62	Case 11	65.40	53.39
Case 2	48.00	45.02	Case 12	68.10	53.76
Case 3	62.10	56.02	Case 13	28.00	34.10
Case 4	64.00	58.61	Case 14	43.40	60.30
Case 5	58.60	63.65	Case 15	67.40	55.48
Case 6	68.00	44.97	Case 16	61.00	55.75
Case 7	68.60	54.17	Case 17	47.00	48.07
Case 8	32.50	46.69	Case 18	58.60	47.48
Case 9	46.00	54.94	Case 19	60.80	63.37
Case 10	66.10	59.74	MAE: 8.96, Pearson Correlation: 0.52		

A deeper analysis is shown in Figure 1 by a Bland-Altman plot. From Y axis, we can see that the systematic error (bias) is around 2.92, meaning that Echonet-Dynamic estimates the EF 2.92% less than the gold standard. Furthermore, in 11 out of 19 cases (57.89 %) the differences are positives, showing that observed EF are greater than estimated EF.

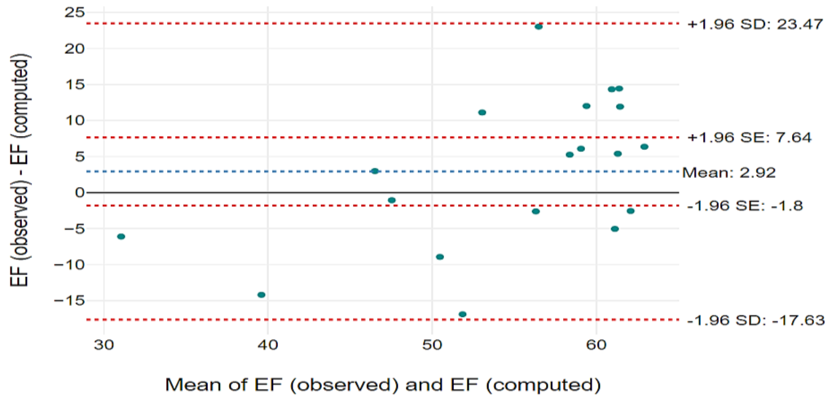

Figure 1: Bland-Altman plot. SD is the standard deviation of the differences and SE is the standard error.

An important aspect of the Bland-Altman plot is the dispersion in the data, where only 5 cases show a difference less than 5 %. Nevertheless, all the points are in the confidence interval of 95 % with respect to the differences, although not in the confidence interval by the standard error regarding the observed EF.

4. Conclusions

This work presented a preliminary study on the use of a pre-trained deep learning method to automatically and unsupervised estimate of the ejection fraction from echocardiograms. Results suggest that is necessary to refine the method. Future works should be in two directions. On one hand, to increase the test dataset to enhance the statistical value of the results. On the other hand, retrain the models considering the acquisition and annotation process of the own dataset. In both directions, it is imperative to construct a bigger dataset in a team work with cardiologists.

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