ORIGINAL PAPER

Efficacy of Artificial Intelligence Software in the Automated Analysis of Left Ventricular Function in Echocardiography in Central Vietnam

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doi: 10.5455/aim.2024.32.32-36.
ACTA INFORM MED. 2024, 32(1): 32-36

Received: JAN 05, 2024
Accepted: FEB 28, 2024

ABSTRACT

Background: In recent years, there has been a significant focus on the development of artificial intelligence (AI) applications in healthcare. However, current scientific evidence is still not convincing enough for the general public and the medical community to widely adopt AI in clinical practice. **Objective**: We conducted this study to investigate the correlation between left ventricular function indices assessed by AI and those evaluated by physicians. **Methods**: This cross-sectional descriptive study was conducted on 136 patients who attended and received treatment at Hue University of Medicine and Pharmacy Hospital from April 2022 to June 2023. Using QLAB version 15, Philips Healthcare. **Results**: The AI software accurately identified 98.5% of the echocardiographic cine-loops. However, there were about 1.5% of cine-loops that the software failed to recognize. The sensitivity of Ejection Fraction (EF) calculated by AI was 73.3%, specificity was 81.3%, and accuracy stood at 78.6%. A strong positive correlation was observed between EF measured by AI and that assessed by physicians, $r = 0.701$, $p < 0.01$. The sensitivity of Global Longitudinal Strain (GLS) calculated by AI was 42.1%, specificity was 84.8%, and accuracy was 67.6%. A moderate positive correlation was found between GLS measured by AI and physician's assessment, $r = 0.460$, $p < 0.01$. **Conclusion**: The use of AI software for evaluating left ventricular function through ejection fraction and global longitudinal strain is rapid and yields results comparable to cardiologists' echocardiographic assessments. The AI-powered software holds a promising and feasible future in clinical practice.

Keywords: Automated software, artificial intelligence, ejection fraction, longitudinal strain.

1. BACKGROUND

Artificial Intelligence (AI) is a vast branch of computer science concerned with the development of intelligent machines capable of performing tasks that typically demand human intelligence. AI finds applications in various domains, including the financial sector, education, supply chain management, manufacturing, retail, and healthcare. In the field of technology,

AI serves as a significant driving force behind numerous innovative business changes. These encompass web searches (e.g., Google), content recommendations (e.g., Netflix), product suggestions (e.g., Amazon), targeted advertising (e.g., Facebook), and autonomous vehicles (e.g., Tesla) (1). AI is expected to significantly impact clinical practice and healthcare services in the near future. AI applications in the medical field encompass symptom matching, patient diagnosis, prognosis, and drug discovery (2).

In recent years, there has been a notable emphasis on the development of AI applications in healthcare, particularly in image-based data. Areas such as radiology, dermatology, pathology, and cardiology have begun to reap the benefits of implementing AI methods. Cardiac image diagnosis, including ultrasound, is also part of this ongoing trend and is advancing rapidly.

Additionally, ultrasound equipment companies are actively driving research and development in AI, introducing new ultrasound techniques into clinical practice, leading to increased complexity in cardiac imaging (3).

Nowadays, cardiovascular diseases are on the rise, life expectancy is increasing, and the burden of cardiac diseases is growing rapidly. Physicians are facing an increasing number of patients and a growing volume of diagnostic results to analyze. In the field of cardiac ultrasound, accurate interpretation often relies heavily on the subjective knowledge of the operator. Cardiac ultrasound bears the burden of dependence on the operator's level of experience, to a greater extent than other imaging modalities such as computed tomography, nuclear imaging, and magnetic resonance imaging. Additionally, non-cardiologists are increasingly using cardiac ultrasound in practice.

AI technology offers new opportunities for cardiac ultrasound to provide more accurate, automated, consistent, time-efficient, and resource-saving interpretations, whether performed by specialized or non-specialized physicians (4). However, current scientific evidence is still not convincing enough for the general public and the medical community to widely adopt AI in clinical practice.

2. OBJECTIVE

In light of this reality, we carried out this study to explore the correlation between AI-automated evaluations of left ventricular function indices and those assessed by specialized cardiac ultrasound physicians

3. MATERIALS AND METHODS

3.1. Study population

A cross-sectional descriptive study was conducted on 136 patients who presented for examination and treatment at Hue University of Medicine and Pharmacy Hospital from April 2022 to June 2023.

Inclusion criteria were individuals who sought medical care and treatment at Hue University of Medicine and Pharmacy Hospital and provided informed consent to participate in the research.

Exclusion criteria were: patients who did not consent to participate in the study; patients with severe valvular heart disease, congenital heart disease, atrial fibrillation, and other life-threatening cardiac arrhythmias; critically ill patients. We used echocardiography with Philips QLAB version 15.0 software (Philips Affiniti 70 Cardiac Ultrasound, Netherlands) to evaluate left ventricular function of the patients at the cardiac ultrasound department of the Cardiovascular Center, Hue University of Medicine and Pharmacy Hospital.

Step 1: Selection of patients for the study based on inclusion and exclusion criteria.

Step 2: Cardiac ultrasound examinations were performed on the patients following a standardized protocol as recommended by the American Society of Echocardiography in 2016 (5). The cardiac ultrasound images were stored in DICOM format.

Step 3: Ejection Fraction (EF) and Global Longitudinal Strain (GLS) were assessed using two methods: A non-specialized cardiac ultrasound technician inputted data into the QLAB 15 software, which integrated artificial intelligence for automatic calculations; Cardiac ultrasound specialists manually performed the measurements using the QLAB 15 software.

3.2. Trans-Thoracic Echocardiography Procedure

In our study, we used the specialized Philips Affiniti 70 cardiac ultrasound machine from the Netherlands, equipped with TM, 2D, Pulsed Doppler, Continuous Wave Doppler, Color Doppler, and Tissue Doppler imaging capabilities. During the procedure, the ultrasound machine simultaneously recorded an electrocardiogram alongside the ultrasound images. Patients were briefed about the examination process, and a clinical cardiac assessment was performed before the ultrasound. Patients rested for at least 5 minutes before the ultrasound.

The machine and power source were checked, and three ECG electrodes were attached to the patient's chest, adjusted for simultaneous ECG recording with ultrasound imaging.

Patient Position

The patient is placed in a left lateral decubitus position at a 90-degree angle to the bed when examining the parasternal views and at a 30-40 degree angle when examining the apical views. Both arms of the patient are raised over the head to expand the intercostal spaces.

Examiner Position

The examiner sits to the right of the patient. They hold a handheld 2.5 or 3.5 MHz electronic sector probe with their right hand, apply ultrasound gel, and begin the examination.

Ultrasound Procedure

The examination is conducted in a sequence that includes 2D, M-mode, color Doppler, pulse-wave Doppler, and tissue Doppler imaging.

Image Capture

Ultrasound images are recorded at a speed of 100 mm/s. Measurements are taken at the end of expiration to minimize the influence of respiratory motion on Doppler spectral analysis. Images of cardiac ultrasound are stored in DICOM format on the machine's hard drive and transferred to a processing workstation using Philips QLAB version 15.0 software.

3.3. Cardiac Ultrasound Data Processing Procedure

Automated Software Evaluation Method

The DICOM files of each patient are input into the QLAB 15 software by a non-specialized ultrasound technician. The input consists of ultrasound slices from recorded 2-chamber and 4-chamber views. The software outputs labeled 2-chamber, 3-chamber, and 4-chamber slices. The machine automatically evaluates EF on the 4-chamber slice and calculates the average GLS on the three automatically selected slices. The technician records the results calculated by the software.

Manual Method

For each patient, the cardiac ultrasound specialist selects 2-chamber, 3-chamber, and 4-chamber slices and uses the tools provided by the QLAB 15 software to manually assess EF on the 4-chamber slice and evaluate GLS for each selected slice, calculating the average GLS.

3.4. Ultrasound Image Quality Assessment Criteria (6)

Good Ultrasound Image Quality

All cardiac regions are clearly observed, and there are no uninterpretable areas. Fair Ultrasound Image Quality: One to two myocardial segments cannot be adequately visualized. Poor Ultrasound Image Quality: More than two myocardial segments are not visualized or are uninterpretable. Criteria for Assessing Abnormal Ejection Fraction and Global Longitudinal Strain (GLS) We employed the criteria from the European Society of Cardiology 2021 to categorize ejection fraction (EF) (7). Subjects with EF <50% were classified into the reduced EF group, and subjects with EF ≥50% were categorized as the normal EF group. A GLS cutoff point of 18% was used, where GLS <18% was considered abnormal, and GLS ≥18% was considered normal (8).

3.5. Data analysis

Data entry and management were conducted using Microsoft Office 365. Statistical algorithms were processed using SPSS software version 26.0. Calculating the frequency and percentage for categorical variables. Statistical significance was considered when $p < 0.05$, highly significant when $p < 0.001$, and very highly significant when $p < 0.0001$. The Shapiro-Wilk and Kolmogorov-Smirnov tests were used to assess the normality of variable distributions.

Linear correlation between two continuous variables was tested using the Pearson correlation for normally distributed variables and the Spearman correlation for non-normally distributed variables.

3.6. Ethical consideration

All patients who met the inclusion criteria and did not fall under the exclusion criteria were invited to participate in the research process. Patients were only included in the research sample if they provided informed consent after a clear explanation of the research method, patient rights, and responsibilities. Patients had the right to withdraw from the research process or request changes to the diagnostic method at any time if desired. Patients were provided with the latest information about the advantages and disadvantages of each diagnostic method. Patient information was encoded to ensure confidentiality and used solely for research purposes.

4. RESULTS

The study was conducted on 136 subjects who met the disease selection criteria according to the research criteria. The 4-chamber section has good, moderate, and poor ultrasound image quality of 47.8%, 39.0%, and 13.2%, respectively. The majority of 3-chamber views have good and moderate image quality, poor quality accounts for 13.2%. In contrast, 2-chamber images had poor image quality accounting for 25.7%, the majority had super moderate image quality at 50% (Table 1).

The AI software's rate of correctly identifying ultrasound sections is 98%. There are 2% of cross-sections that the software cannot recognize. The software automatically identifies the correct 4-chamber cross-section in 136/136 patients, a rate of 100%. For the 2-chamber view, the software correctly identified 133/136 patients (97.8%). The software automatically identified 133/136 (Table 2). There is a strong positive correlation between EF on echocardiography measured by AI and measured by the sonographer, $r = 0.701$, $p < 0.01$ (Figure 1). There is a moderate positive correlation between GLS on echocardiography measured by AI and measured by the sonographer, $r = 0.460$, $p < 0.01$ (Figure 2).

Characteristic	4 chambers		3 chambers		2 chambers	
	n	%	n	%	n	%
Good ultrasound image quality	65	47.8	46	33.8	33	24.3
Moderate ultrasound image quality	53	39.0	72	52.9	68	50.0
Poor ultrasound image quality	18	13.2	18	13.2	35	25.7

Table 1. Characteristics of echocardiographic image quality

	Realistic ultrasound cross section of the patient		
Ultrasound section determined by the software	2 chambers	3 chambers	4 chambers
Correct identification	133	133	136
Wrong identification	3	3	0

Table 2. AI's ability to recognize and classify ultrasound sections

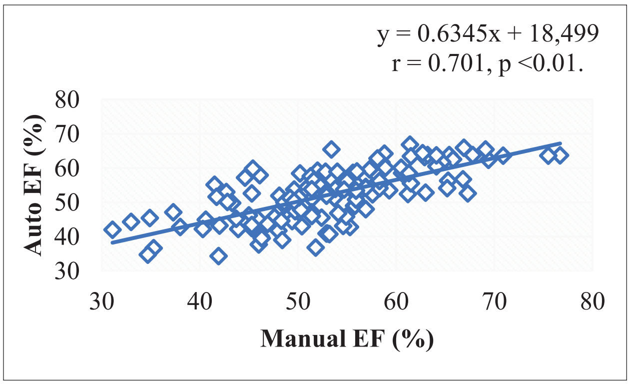

Figure 1. Correlation between AI-measured EF and sonographer-measured EF.

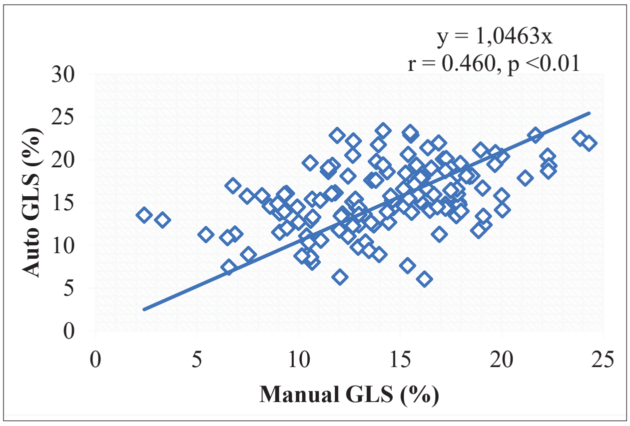

Figure 2. Correlation between GLS measured by AI and measured by sonographers.

5. DISCUSSION

Echocardiography is a non-invasive diagnostic method that helps evaluate the structure and function of the heart. Echocardiography has many advantages such as real-time assessment of cardiac function, can be performed multiple times, available means and low cost (9).

However, the biggest disadvantage of echocardiography is that its accuracy depends heavily on the skills and experience of the ultrasound technician. Automated evaluation of echocardiographic images using AI offers new opportunities for physicians to provide more accurate, automated, consistent, and faster results (4).

In this study, we evaluated the ability to identify cross-sections on echocardiography. The results were very impressive when the software correctly identified the ultrasound cross-sections quickly with a high rate of 98%. The software correctly identifies 2-chamber, 3-chamber, and 4-chamber cross-sections at rates of 98%, 98%, and 100%, respectively. Research by Ivar M. Salte and colleagues in 2021 also showed that the rate of correct identification of heart chambers was 97% (6).

However, upon further analysis, we found that AI can correctly identify 100% of echocardiographic sections if the images are of good quality. Through this, our AI software can automatically classify echocardiographic cross-sections, equivalent to that of an echocardiographer. Analyzing standard echocardiographic cross-sectional images is the foundation for accurate analysis of echocardiographic parameters.

Our study results show that there is a strong positive correlation between EF assessed by doctors and assessed by AI software (r=0.701 and p<0.01). At the same time, GLS strength assessed by doctors and assessed by AI software also has a positive correlation (r = 0.46, and p < 0.01). Through our results and the results of many studies, it has been shown that automatic EF and GLS values using AI software have quite high accuracy, equivalent to results performed by echocardiographers (6, 10). However, most of the research and software used are only being updated in 2021. Currently, new and better updated software promises to produce better analytical results, approaching professional expertise. echocardiographer.

Characteristics of AI include self-learning ability, adaptability and error tolerance. The more input data, the higher the accuracy. Application developers have built big data systems to build better echocardiography applications such as CAMUS big data, EchoNet Dynamic big data, and CardiacPhase. EchoNet-Dynamic is a deep learning algorithm developed using 10,030 echocardiograms from Stanford University Medical Center. The more data AI has access to, the more accurate AI is in data analysis (11, 12).

AI software only takes a few seconds to analyze right ventricular systolic function, while evaluating heart function by a doctor must go through many steps and take a lot of time. To evaluate heart function using ultrasound to mark myocardial tissue, the sonographer measures GLS using a routine method in 5-7 minutes per section.

In contrast, AI assessment only takes a few seconds for each cross section. With the application of AI in assessing left ventricular function, the results obtained are highly accurate, shortening the doctor's ultrasound examination time. These deep learning methods are implemented into the ultrasound machine, individual steps of the AI process can be calculated during image acquisition, allowing for rapid analysis at the bedside and even further analysis. real-time measurement on an ultrasound scanner without the need for ultrasound experts (6).

Currently, most recently the software company Us2.AI has deployed the evaluation of echocardiography results in real time quickly and accurately. In addition, some applications allow medical staff, who are not sonographers, to accurately perform echocardiography under direct real-time AI guidance (12, 13).

Promising advances in AI applications can hopefully convince the medical community to widely use AI in clinical practice in general and the field of echocardiography in particular.

Limitations of the study

Our study contains some limitations. We only used software from one vendor. We have not compared other software from different companies. Furthermore, the software used is not open source. We cannot conclude whether one measurement system in this study is more accurate than the other. The reliability of echocardiographic measurements depends on many factors related to both image acquisition. Therefore, the present study was not designed to determine the influence of image acquisition on measurement reproducibility. Further research is needed to address the limitations mentioned before AI-induced measurements can be routinely used in clinical settings. However, we find the present results promising both in terms of feasibility and agreement with the reference method.

6. CONCLUSION

Using artificial intelligence software to evaluate left ventricular systolic function using ejection fraction index and global longitudinal strain quickly and provides results comparable to echocardiographers. Software using artificial intelligence has a promising future and is feasible for application in clinical practice.

- **Declaration of patient consent:** The authors certify that they have obtained all appropriate patient consent forms.
- **Author's contribution:** DCT, LVT, DNNH and TNV gave a substantial contribution to the conception and design of the work. DCT and DNNH gave a substantial contribution of data. DCT and DNNH gave a substantial contribution to the acquisition, analysis, or interpretation of data for the work. DCT, LVT, DNNH and TNV had a part in article preparing for drafting or revising it critically for important intellectual content. All authors gave final approval of the version to be published and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.
- **Financial support and sponsorship:** Nil.
- **Conflicts of interest:** There are no conflicts of interest.

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