Medical Science

Advancing cardiac care: The role of Artificial Intelligence in modern echocardiography - A review

Anita Król[1*], Jakub Pudźwa[2], Kamil Gibczyński[1], Aleksandra Roztoczyńska[2], Aleksandra Jeńć-Magoń[2], Martyna Orzechowska[2], Karolina Jabłońska[2], Piotr Paluch[2], Karol Leśniewski[2], Michał Orczyk[2]

To Cite:
Król A, Pudźwa J, Gibczyński K, Roztoczyńska A, Jeńć-Magoń A, Orzechowska M, Jabłońska K, Paluch P, Leśniewski K, Orczyk M. Advancing cardiac care: The role of Artificial Intelligence in modern echocardiography - A review. *Medical Science* 2025; 29: e27ms3523
doi: https://doi.org/10.54905/disssi.v29i156.e27ms3523

Authors' Affiliation:
[1]Fryderyk Chopin University Clinical Hospital in Rzeszów, ul. Fryderyka Szopen 2, 35-055 Rzeszów, Poland
[2]College of Medical Sciences, University of Rzeszów Tadeusza Rejtana 16c Ave, 35-310 Rzeszów, Poland

[*]Corresponding Author
Fryderyk Chopin University Clinical Hospital in Rzeszów, ul. Fryderyka Szopen 2, 35-055 Rzeszów,
Poland
Email: anitakrol98@gmail.com

ORCID List

Anita Król	0009-0004-4272-9403
Jakub Pudźwa	0009-0003-1025-8304
Kamil Gibczyński	0009-0006-6968-4684
Aleksandra Roztoczyńska	0009-0001-3340-8585
Aleksandra Jeńć-Magoń	0009-0003-2340-6505
Martyna Orzechowska	0000-0001-6366-5761
Karolina Jabłońska	0000-0001-7454-5263
Piotr Paluch	0009-0001-0126-6850
Karol Leśniewski	0009-0000-5704-4483
Michał Orczyk	0000-0002-2707-7994

Peer-Review History
Received: 12 October 2024
Reviewed & Revised: 16/October/2024 to 27/January/2025
Accepted: 31 January 2025
Published: 07 February 2025

Peer-review Method
External peer-review was done through double-blind method.

Medical Science
pISSN 2321–7359; eISSN 2321–7367

DISCOVERY SCIENTIFIC SOCIETY

ABSTRACT

Echocardiography is one of the most accessible and versatile tools in cardiac imaging. It offers excellent diagnostic value for a wide range of cardiovascular diseases. However, the dependence on operator skill and the long time required to take and interpret measurements correctly can limit its efficiency. Artificial intelligence (AI), through machine learning (ML) and deep learning (DL), promises a solution to these challenges. It can assist in image acquisition, interpretation, analysis, and diagnostics and be used to train expert and novice clinicians. Despite the potential of AI-assisted echocardiography, many weaknesses remain, including small and non-diverse datasets used in research studies, the "black-box" nature of DL algorithms, and ethical concerns. With further research, AI has the potential to streamline echocardiographic workflows, enhance diagnostic precision, and make cardiovascular care more accessible and efficient.

Keywords: Echocardiography, artificial intelligence, cardiovascular diagnostics, deep learning, machine learning

1. INTRODUCTION

Through the years, echocardiography has remained one of the most valuable and widely accessible tools for cardiac imaging (Papolos et al., 2016). It is relatively cost-effective, non-radioactive, and offers real-time results, making it instrumental in diagnosing various cardiovascular diseases, such as valvular defects, heart failure, cardiomyopathies, and congenital abnormalities, and evaluating the effects of already implemented treatments (Via et al., 2014). Despite its benefits, echocardiography is not without limitations. The operator's competence can significantly impact the examinations' accuracy, which can cause differences in image interpretation (De-Geer et al., 2015).

Intra- and inter-operator variability is a significant challenge, which creates a need for an objective, automated diagnostic system. Additional drawbacks of echocardiography include a low signal-to-noise ratio, inconsistent image quality, and a lower level of reproducibility. Manual measurements and image evaluations can require significant time, resources, and competence (Lang et al., 2015). Artificial intelligence (AI) offers a promising solution to these challenges and has found widespread application in echocardiographic research.

Through machine learning (ML) and deep learning (DL), AI can learn from processed data, identify patterns, and make informed predictions. AI-driven automation has the potential to accelerate and enhance various echocardiographic procedures by improving image acquisition, automating measurements, increasing diagnostic precision, creating new diagnostic patterns, and mitigating human error (Motwani et al., 2017). This review presents the current state of AI in echocardiography, highlighting its benefits, challenges, and future potential.

2. METHODOLOGY

This review examines using artificial intelligence (AI) in echocardiography by identifying, analyzing, and synthesizing relevant studies. We searched peer-reviewed literature using electronic databases, including PubMed, Scopus, IEEE Xplore, and Google Scholar. The search covered studies published from January 2014 to August 2024. Keywords and search terms included "AI in echocardiography", "machine learning in cardiac imaging", "deep learning for cardiovascular diagnostics", and "automated cardiac function assessment". To ensure the quality of the cited studies, we excluded non-peer-reviewed articles, abstracts, or editorials, papers focusing only on theoretical models without practical application in echocardiography, and studies not available in full text.

3. RESULT AND DISCUSSION

Artificial intelligence overview

Artificial Intelligence (AI) studies computational algorithms that can perform human-like tasks such as problem-solving, formulating analyses, and decision-making (Iezzi et al., 2019). In recent years, its use has started to be widely researched and implemented in various medical fields, mainly due to pattern and object recognition as well as identification. It creates value for AI in disease prognosis, helping to develop treatment plans and offering prognostic data (Gulshan et al., 2016; Chilamkurthy et al., 2018; Krittanawong et al., 2021). AI evolution, beginning in the 1950s, has introduced two main concepts - machine learning (ML) and its subset deep learning (DL).

ML models analyze data, learn from it, and then make predictions or decisions based on it. They are also able to provide predictions based on new, unseen data. There are three main categories of ML - supervised, reinforced, and unsupervised ML (Table 1). In supervised learning, the model learns from labeled data, meaning each input has to come with a corresponding output. Unsupervised learning occurs when the model is given unlabeled data, and must find patterns and structures within it. In contrast, systems employ reinforcement learning by receiving input and output data and acquiring specific behaviors through trial-and-error processes, which are optimized using a reward signal.

ML needs significantly less input data than DL models but is better suited for more straightforward tasks (Krittanawong et al., 2023; Johnson et al., 2018). DL, a subset of ML, uses more complex architectures like deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN). These enable it to learn intricate patterns directly from raw data without human intervention. The end-to-end learning capability of DL models eliminates the need for labor-intensive manual feature engineering (Johnson et al., 2018).

Table 1 Key differences between common ML types

	Type of ML	Data type	Goal
MACHINE LEARNING	Supervised learning	Pre-labeled data - each input has an output	Learn to predict outputs for unseen inputs
	Unsupervised learning	Unlabeled data - only inputs, no	Find patterns and relationships and,

		labeled outputs	based on them, separate data into clusters or groups
	Reinforcement learning	No predefined dataset - interactions with the environment	Learn optimal actions through trial-and-error.

Ai-Algorithms in echocardiographic imaging

Image Analysis and Measurements

One of the main aspects of echocardiography is the assessment of left ventricular (LV) function and size. Left ventricular ejection fraction (LVEF) and LV systolic and diastolic function carry significant prognostic value. However, their measurements are subjected to operator bias and difficulties with proper image acquisition and correct measurement, making the results variable between operators (Mitchell et al., 2019). Tromp et al., (2022) created an automated model to segment cardiac chambers with a segmentation accuracy of 93,0-94,3% for the left atrium and left ventricle. It was able to correctly classify systolic dysfunction presented as LVEF < 40% with area under the operating curve (AUC) 0.90-0.96 and diastolic dysfunction (E/e' ratio - the ratio of early diastolic mitral inflow velocity to early diastolic mitral annulus velocity) with AUC 0.91-0.96 depending on the dataset.

These results suggest that this DL model can provide a diagnostic level of accuracy. With an individual equivalence coefficient (IEC) less than 0 for all measurements, the AI algorithm created greater predictability than human experts in this study (Tromp et al., 2022). Compared to LVEF, there is a more accurate and reproducible assessment of myocardial function - global longitudinal strain (GLS). Strain imaging is time-consuming and prone to deviation based on the operator's experience - its analysis could take roughly 5 to 10 minutes (Barbier et al., 2015). Deng et al., (2022) proposed a CNN for myocardial segmentation and motion estimation. They used 105 video sequences from an existing database to teach the algorithm and 150 videos from one hospital to evaluate the model's effectiveness.

The results were comparable between DL algorithms and traditional methods, promising for real-time clinical applications and enhanced diagnostic efficiency (Deng et al., 2022). Similarly, Salte et al., (2021) designed a DL model to measure GLS and compare the results to the standard speckle-tracking software. The presented results were minimally different between the two methods, with a mean absolute difference of 1,8%. The time difference, however, was drastic - the AI model took up to 15 seconds per exam, while the conventional model took 5-10 minutes to produce results (Salte et al., 2021).

Automated echocardiographic exams

AI-driven tools streamline processes such as image acquisition, annotation, and report generation, reducing clinicians' workload and improving efficiency. For instance, in Zhang et al., (2018) successfully demonstrated a DL model for echocardiogram interpretation capable of view classification, image segmentation, cardiac structure and function quantification, and disease detection. The algorithm, trained on over 14,000 echocardiograms using convolutional neural networks (CNNs), achieved 96% accuracy in classifying the parasternal long axis (PLAX) view. Additionally, it estimated key cardiac structural parameters, such as left ventricular (LV) mass, diastolic volume, and left atrial (LA) volume, with mean absolute deviations ranging from 15% to 17%.

The researchers successfully trained the CNNs to detect hypertrophic cardiomyopathy, cardiac amyloidosis, and pulmonary artery hypertension, with an accuracy of 85-93%. Although its diagnostic accuracy did not reach expert performance, it showed promise (Zhang et al., 2018). Another study developed the Dimensional Reconstruction of Imaging Data (DROID) model to automate measurements of LA and LV structures and functions, associating these measurements with incident cardiovascular outcomes. The model performed four classification tasks on over 60,000 echocardiograms, the first being the detection of image type - choosing from 2 dimensions B mode, Doppler or 3-dimensional images - area under the curve (AUC) on all of them was 1.0.

The following tasks were estimating image quality - good vs. poor and determining axis - on vs. off - in both AUC values were 0,87 - and view classification. Based on the gathered data, the AI model was also taught to predict possible cardiovascular outcomes. A 1-SD decrease in LVEF was associated with a 43% greater risk of heart failure (Hazard Ratio [HR]: 1.43; 95% CI: 1.23-1.66). A 1-SD decrease in LVEF increased atrial fibrillation (AF) risk by 19% (HR: 1.19; 95% CI: 1.10-1.27). A 1-SD decrease in LVEF was associated with a 17% increased risk of death (HR: 1.17; 95% CI: 1.06-1.30). The AI outperformed traditional human echocardiographic reports in predicting outcomes, showing greater consistency and stronger associations with heart problems (Lau et al., 2023).

Narang et al., (2021) offered an interesting perspective on the automatization of echocardiography in their multi-center diagnostic study. Eight nurses with no prior expertise in echocardiography were trained with an AI model for only one hour before taking study exams. AI provided real-time guidance during the scans, significantly reducing the need for extensive training or expert supervision. Nurses acquired diagnostic-quality scans for left ventricular size, function, and pericardial effusion in 98.8% of cases and right ventricular size in 92.5%. Their scans were nearly as accurate as sonographers' for core diagnostic parameters, highlighting AI's potential to aid non-expert healthcare workers in diagnostic services (Narang et al., 2021).

Diagnostic capabilities

Apart from general echocardiographic exams, efforts to diagnose specific conditions with AI also have been noted. Due to its pattern recognition capabilities, DL algorithms can analyze subtle changes in the morphology and function of the myocardium, which might be too miniscule for a human observer. Left ventricular hypertrophy (LVH) is a common heart condition caused by many diseases. It is also a prognostic factor for cardiovascular events. Standard echocardiography allows its detection in the early stages, although the exam results can vary between the operators. With this in mind, efforts have been made to create reliable and objective automatic systems.

Yu et al., (2022) proposed a DL framework trained on over 1610 transthoracic echocardiograms to detect LVH and its etiology-hypertrophic cardiomyopathy (HCM), cardiac amyloidosis (CA), and hypertensive heart disease (HHD). Compared to diagnoses made by two experienced clinicians, the AI model yielded better results in distinguishing LVH and its etiology. The network demonstrated superior accuracy (96.2%) compared to two echocardiographers (84.6%) in detecting LVH. Similarly, differentiating the etiology of LVH - specialists had an accuracy of 55,2%, whereas the network had 80,4%. The AI network performed better than echocardiographers in LVH detection and etiology classification (Yu et al., 2022).

Similarly, another study created a CNN model to diagnose LVH, among others, with an AUC of 0,75 (Ghorbani et al., 2020). Another common cardiac disease associated with morbidity and mortality is aortic stenosis (AS). Ordinarily, the diagnosis uses Doppler echocardiography, which requires time and operator skills. Seeing the growing need for a quick and easily accessible AS diagnostic tool, Holste et al., (2023) used a DL model to presume the presence of AS based only on PLAX videos without the Doppler input. Researchers introduced the DL architecture to approximately 37,000 transthoracic echocardiogram videos comprising 16 consecutive frames. It performed remarkably with AUC 0.92-0.98 with high sensitivity (85%) and specificity (96%).

Their findings have great potential to improve early detection and monitoring of AS and enable widespread screening in primary care or emergency settings (Holste et al., 2023). A separate study, this one using both two-dimensional and Doppler images, offered similar results. Measurements taken by an already pre-existing, FDA-approved artificial neural network called Us2.ai were compared to the findings of trained echocardiographers, showing a strong correlation between the two. Parameters like peak velocity (Vmax) and mean pressure gradient (MPG) showed almost perfect resemblance. Lower accuracy for the left ventricular outflow tract diameter (LVOTd) and its higher exclusion rate indicates that this particular parameter can be challenging for human and AI models.

Further studies and improvement in this area are needed (Krishna et al., 2023). One of the causes of AS is a process called aortic valve calcification. It progresses rather slowly, requiring several echocardiographic exams or computed tomography scans through the years. Elvas et al., (2024) created a CNN model to locate the aortic valve on the parasternal short-axis view and identify its calcium structures with a precision of 95% and 92%, respectively. The main challenge of their work was the slim database used - only 61 images. With promising results, the algorithm requires application to more extensive and more diverse databases to validate its effectiveness.was created (Elvas et al., 2024).

Katsushika et al., (2021) tried to combat the problem of the diagnosis of cardiac sarcoidosis (CS). For being the leading cause of death in patients with sarcoidosis, its examination can be complex, consisting of many tests, one of them being echocardiography. However, although there are findings specific to CS in echocardiography, the sensitivity of performed exams can be pretty low - reportedly even 12,6 %. The group used an existing algorithm, initially used for LVEF measurements, modifying it to detect CS. The study used 302 videos, 151 of which came from 50 CS patients, and the rest were from a control group. The results, performed on the set of 41 additional echocardiographic movies, were comparable to examinations conducted by five experienced specialists - the pre-trained algorithm had an AUC of 0.842, while the cardiologists had an AUC of 0.855.

This CNN model might be a valuable tool for CS detection. However, more experimentation is still needed, preferably on a more extensive database (Katsushika et al., 2021). The clinical implementation of AI systems in echocardiography has made promising advancements. Tools such as Ultromics' EchoGo Heart-failure and EchoGo Amyloidosis received FDA approval for aiding in the diagnosis of heart failure with preserved ejection fraction and cardiac amyloidosis. These devices are primarily intended to support clinicians in making decisions and improving diagnostic precision, which may result in earlier interventions and better patient outcomes (FDA, 2020; FDA, 2024).

Challenges and ethical considerations

The implementation of AI in echocardiography faces several methodological and ethical challenges. Data quality and size are significant limitations, with many studies relying on small, non-diverse datasets, which can lead to biased outcomes and reduce model generalizability. DL models taught on small datasets can create incorrect results that mislead clinicians and negatively impact patient care. To address and combat data size issues, researchers can use transfer learning - ML subtype in which an existing algorithm, pre-trained on a more extensive database, is adapted to meet new needs and applied to a smaller database (Shin et al., 2016; Katsushika et al., 2021). Additionally, multi-center, multi-vendor studies are essential to ensure diverse and comprehensive datasets and provide generalizability of created models.

Another disadvantage of DL algorithms is the lack of interpretability - the "black-box" problem. While the models can make exact predictions or classifications, the specific pathways through which they arrive at these outcomes are often challenging for humans to conceptualize (Krittanawong et al., 2019). It can hinder the findings' reproducibility and cause bias detection problems. Because of these, it can be challenging for practitioners to trust their results without knowing and understanding exactly how the models work. In contrast, over-reliance on AI tools could cause deskilling among clinicians. Creating algorithms should be implemented into medical education to better understand and apply DL networks to their clinical work and research basics of ML understanding.

A relationship between cardiologists and AI engineers is essential to optimize results and create a mutual understanding. Furthermore, there are legal and ethical concerns about using AI in medicine. The large databases required by the DL models may include sensitive patient information and be vulnerable to potential security breaches, which can result in data leaks or misuse of data for non-medical purposes. Over time, patients may grow concerned about the safety of their information, which can limit the data they provide. Using large datasets presents its own set of challenges. Many echocardiography datasets are not widely available, and creating new ones can be costly and time-consuming (Krittanawong et al., 2019).

4. CONCLUSIONS

Echocardiography presents many benefits compared to other imaging methods, but valuable usage demands extensive training and operator time. AI, particularly deep learning architectures, has great potential to assist echocardiographers, making their job easier - improving diagnostic accuracy and efficiency. DL-driven echocardiography has the potential to revolutionize and redefine cardiovascular care by allowing earlier disease detection, personalized treatment planning, and broader accessibility to echocardiography. However, data quality, interpretability, and ethical considerations must be resolved to guarantee safe and successful clinical integration. Future research should concentrate on large-scale, diversified datasets, interdisciplinary collaborations, and educational projects to raise patient care and streamline workflow.

Authors Contribution

Conceptualization: Anita Król

Methodology, Formal analysis, Investigation, Writing – original draft: Anita Król, Jakub Pudźwa, Kamil Gibczyński, Aleksandra Roztoczyńska, Aleksandra Jeńć-Magoń, Martyna Orzechowska, Karolina Jabłońska, Piotr Paluch, Karol Leśniewski, Michał Orczyk

Writing – review and editing: Anita Król, Jakub Pudźwa

Visualization: Anita Król, Jakub Pudźwa

All authors have read and agreed with the published version of the manuscript.

Acknowledgments

Not applicable.

Ethical approval
Not applicable.

Informed consent
Not applicable.

Funding
This study has not received any external funding.

Conflict of interest
The authors declare that there is no conflict of interests.

Data and materials availability
All data sets collected during this study are available upon reasonable request from the corresponding author.

REFERENCES

1. Barbier P, Mirea O, Cefalù C, Maltagliati A, Savioli G, Guglielmo M. Reliability and feasibility of longitudinal AFI global and segmental strain compared with 2D left ventricular volumes and ejection fraction: intra- and inter-operator, test–retest, and inter-cycle reproducibility. Eur Heart J Cardiovasc Imaging 2015; 16(6):642–652. doi: 10.1093/ehjci/jeu274
2. Chilamkurthy S, Ghosh R, Tanamala S, Biviji M, Campeau NG, Venugopal VK, Mahajan V, Rao P, Warier P. Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. Lancet 2018; 392(10162):2388-2396. doi: 10.1016/S0140-6736(18)31645-3
3. De-Geer L, Oscarsson A, Engvall J. Variability in echocardiographic measurements of left ventricular function in septic shock patients. Cardiovasc Ultrasound 2015; 13:19. doi: 10.1186/s12947-015-0015-6
4. Deng Y, Cai P, Zhang L, Cao X, Chen Y, Jiang S, Zhuang Z, Wang B. Myocardial strain analysis of echocardiography based on deep learning. Front Cardiovasc Med 2022; 9:1067760. doi: 10.3389/fcvm.2022.1067760
5. Elvas LB, Gomes S, Ferreira JC, Rosário LB, Brandão T. Deep learning for automatic calcium detection in echocardiography. BioData Min 2024; 17:1–19. doi: 10.1186/s13040-024-00381-1
6. FDA. FDA authorizes marketing of first cardiac ultrasound software that uses artificial intelligence to guide user. U.S. Food and Drug Administration 2020.
7. FDA. FDA Roundup: November 19, 2024. U.S. Food and Drug Administration 2024.
8. Ghorbani A, Ouyang D, Abid A, He B, Chen JH, Harrington RA, Liang DH, Ashley EA, Zou JY. Deep learning interpretation of echocardiograms. NPJ Digit Med 2020; 3:10. doi: 10.1038/s41746-019-0216-8
9. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, Venugopalan S, Widner K, Madams T, Cuadros J, Kim R, Raman R, Nelson PC, Mega JL, Webster DR. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA 2016; 316(22):2402-2410. doi: 10.1001/jama.2016.17216
10. Holste G, Oikonomou EK, Mortazavi BJ, Coppi A, Faridi KF, Miller EJ, Forrest JK, McNamara RL, Ohno-Machado L, Yuan N, Gupta A, Ouyang D, Krumholz HM, Wang Z, Khera R. Severe aortic stenosis detection by deep learning applied to echocardiography. Eur Heart J 2023; 44(43):4592-4604. doi: 10.1093/eurheartj/ehad456
11. Iezzi R, Goldberg SN, Merlino B, Posa A, Valentini V, Manfredi R. Artificial Intelligence in Interventional Radiology: A Literature Review and Future Perspectives. J Oncol 2019; 2019:6153041. doi: 10.1155/2019/6153041
12. Johnson KW, Torres SJ, Glicksberg BS, Shameer K, Miotto R, Ali M, Ashley E, Dudley JT. Artificial Intelligence in Cardiology. J Am Coll Cardiol 2018; 71(23):2668-2679. doi: 10.1016/j.jacc.2018.03.521
13. Katsushika S, Kodera S, Nakamoto M, Ninomiya K, Kakuda N, Shinohara H, Matsuoka R, Ieki H, Uehara M, Higashikuni Y, Nakanishi K, Nakao T, Takeda N, Fujiu K, Daimon M, Ando J, Akazawa H, Morita H, Komuro I. Deep Learning Algorithm to Detect Cardiac Sarcoidosis from Echocardiographic Movies. Circ J 2021; 86(1):87-95. doi: 10.1253/circj.CJ-21-0265

14. Krishna H, Desai K, Slostad B, Bhayani S, Arnold JH, Ouwerkerk W, Hummel Y, Lam CSP, Ezekowitz J, Frost M, Jiang Z, Equilbec C, Twing A, Pellikka PA, Frazin L, Kansal M. Fully Automated Artificial Intelligence Assessment of Aortic Stenosis by Echocardiography. J Am Soc Echocardiogr 2023; 36(7):769-777. doi: 10.1016/j.echo.2023.03.008
15. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U, Min JK, Tang WHW, Halperin JL, Narayan SM. Deep learning for cardiovascular medicine: a practical primer. Eur Heart J 2019; 40(25):2058-2073. doi: 10.1093/eurheartj/ehz056
16. Krittanawong C, Omar A, Narula S, Sengupta PP, Glicksberg BS, Narula J, Argulian E. Deep learning for echocardiography: Introduction for clinicians and future vision: State-of-the-art review. Life 2023; 13:1029. doi: 10.3390/life13041029
17. Krittanawong C, Virk HUH, Kumar A, Aydar M, Wang Z, Stewart MP, Halperin JL. Machine learning and deep learning to predict mortality in patients with spontaneous coronary artery dissection. Sci Rep 2021; 11(1):8992. doi: 10.1038/s41598-021-88172-0
18. Lang RM, Badano LP, Mor-Avi V, Afilalo J, Armstrong A, Ernande L, Flachskampf FA, Foster E, Goldstein SA, Kuznetsova T, Lancellotti P, Muraru D, Picard MH, Rietzschel ER, Rudski L, Spencer KT, Tsang W, Voigt JU. Recommendations for cardiac chamber quantification by echocardiography in adults: an update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging. J Am Soc Echocardiogr 2015; 28(1):1-39.e14. doi: 10.1016/j.echo.2014.10.003
19. Lau ES, Di-Achille P, Kopparapu K, Andrews CT, Singh P, Reeder C, Al-Alusi M, Khurshid S, Haimovich JS, Ellinor PT, Picard MH, Batra P, Lubitz SA, Ho JE. Deep Learning-Enabled Assessment of Left Heart Structure and Function Predicts Cardiovascular Outcomes. J Am Coll Cardiol 2023; 82(20):1936-1948. doi: 10.1016/j.jacc.2023.09.800
20. Mitchell C, Rahko PS, Blauwet LA, Canaday B, Finstuen JA, Foster MC, Horton K, Ogunyankin KO, Palma RA, Velazquez EJ. Guidelines for Performing a Comprehensive Transthoracic Echocardiographic Examination in Adults: Recommendations from the American Society of Echocardiography. J Am Soc Echocardiogr 2019; 32(1):1-64. doi: 10.1016/j.echo.2018.06.004
21. Motwani M, Dey D, Berman DS, Germano G, Achenbach S, Al-Mallah MH, Andreini D, Budoff MJ, Cademartiri F, Callister TQ, Chang HJ, Chinnaiyan K, Chow BJ, Cury RC, Delago A, Gomez M, Gransar H, Hadamitzky M, Hausleiter J, Hindoyan N, Feuchtner G, Kaufmann PA, Kim YJ, Leipsic J, Lin FY, Maffei E, Marques H, Pontone G, Raff G, Rubinshtein R, Shaw LJ, Stehli J, Villines TC, Dunning A, Min JK, Slomka PJ. Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. Eur Heart J 2017; 38(7):500-507. doi: 10.1093/eurheartj/ehw188
22. Narang A, Bae R, Hong H, Thomas Y, Surette S, Cadieu C, Chaudhry A, Martin RP, McCarthy PM, Rubenson DS, Goldstein S, Little SH, Lang RM, Weissman NJ, Thomas JD. Utility of a Deep-Learning Algorithm to Guide Novices to Acquire Echocardiograms for Limited Diagnostic Use. JAMA Cardiol 2021; 6(6):624-632. doi: 10.1001/jamacardio.2021.0185
23. Papolos A, Narula J, Bavishi C, Chaudhry FA, Sengupta PP. U.S. Hospital Use of Echocardiography: Insights from the Nationwide Inpatient Sample. J Am Coll Cardiol 2016; 67(5):502-11. doi: 10.1016/j.jacc.2015.10.090
24. Salte IM, Østvik A, Smistad E, Melichova D, Nguyen TM, Karlsen S, Brunvand H, Haugaa KH, Edvardsen T, Lovstakken L, Grenne B. Artificial Intelligence for Automatic Measurement of Left Ventricular Strain in Echocardiography. JACC Cardiovasc Imaging 2021; 14(10):1918-1928. doi: 10.1016/j.jcmg.2021.04.018
25. Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, Yao J, Mollura D, Summers RM. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Trans Med Imaging 2016; 35(5):1285-98. doi: 10.1109/TMI.2016.2528162
26. Tromp J, Seekings PJ, Hung CL, Iversen MB, Frost MJ, Ouwerkerk W, Jiang Z, Eisenhaber F, Goh RSM, Zhao H, Huang W, Ling LH, Sim D, Cozzone P, Richards AM, Lee HK, Solomon SD, Lam CSP, Ezekowitz JA. Automated interpretation of systolic and diastolic function on the echocardiogram: a multicohort study. Lancet Digit Health 2022; 4(1):e46-e54. doi: 10.1016/S2589-7500(21)00235-1
27. Via G, Hussain A, Wells M, Reardon R, ElBarbary M, Noble VE, Tsung JW, Neskovic AN, Price S, Oren-Grinberg A, Liteplo A, Cordioli R, Naqvi N, Rola P, Poelaert J, Gulič TG, Sloth E, Labovitz A, Kimura B, Breitkreutz R, Masani N, Bowra J, Talmor D, Guarracino F, Goudie A, Xiaoting W, Chawla R, Galderisi M, Blaivas M, Petrovic T, Storti E, Neri L, Melniker L; International Liaison Committee on Focused Cardiac UltraSound (ILC-FoCUS); International Conference on Focused Cardiac UltraSound (IC-FoCUS). International evidence-based recommendations for focused cardiac ultrasound. J Am Soc Echocardiogr 2014; 27(7):683.e1-683.e33. doi: 10.1016/j.echo.2014.05.001

28. Yu X, Yao X, Wu B, Zhou H, Xia S, Su W, Wu Y, Zheng X. Using deep learning method to identify left ventricular hypertrophy on echocardiography. Int J Cardiovasc Imaging 2022; 38(4):759-769. doi: 10.1007/s10554-021-02461-3
29. Zhang J, Gajjala S, Agrawal P, Tison GH, Hallock LA, Beussink-Nelson L, Lassen MH, Fan E, Aras MA, Jordan C, Fleischmann KE, Melisko M, Qasim A, Shah SJ, Bajcsy R, Deo RC. Fully Automated Echocardiogram Interpretation in Clinical Practice. Circulation 2018; 138(16):1623-1635. doi: 10.1161/CIRCULATIONAHA.118.034338