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Artificial Intelligence in cardiovascular medical imaging

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Abstract: *Artificial Intelligence (AI) has become an important tool for computer-aided diagnosis of medical imaging. This review aims to provide an overview for clinicians, explaining the relevant aspects of artificial intelligence and machine learning (ML) and presenting up-to-date applications of AI and ML techniques to medical imaging methods such as angiography, magnetic resonance, and echocardiography.*

For each imaging method, we present the acquisition process, the types of diagnostic test interpretation, and the challenges related to them, as well as how AI/ML techniques, have improved the process of decision making.

A summary of selected works applying AI/ML techniques to medical imaging is organized into a table, which highlights the scope of the study, the dataset used, the details of each approach as well as the measured results, including objectives and criteria. The overall benefits of AI in medical imaging are extracted based on the diverse applications and high evaluation scores. In the end, cardiologists should have an advanced understanding of using AI to integrate clinical data and making the final decision in diagnosis.

Keywords: *machine learning, cardiology, angiography, echography*

INTRODUCTION

The application of AI algorithms to a data set has the usual initial steps of developing the algorithm's ability to "learn" based on the training data and to apply the knowledge gained in making predictions. The “learning phase” of an algorithm consists of an incremental optimization of the model parameters with which it is configured, so that performance on a given training objective (e.g. classification of the most likely diagnosis, regression of numerical value of a health parameter) increases.

Machine Learning is a methodology used to recognize such patterns; the applicability of this can be extended very well in the context of medical imaging. Usually, this technique starts with the use of an ML-based system that determines those characteristics of the images that are considered to be important in making the prediction or diagnosis. As a result, the system identifies the best combination of these characteristics for the image classification and computes statistical data for the different regions identified.

The last decade demonstrates the huge potential of machine learning techniques in many domains along with the development of the graphical processing units (CPU/GPU),

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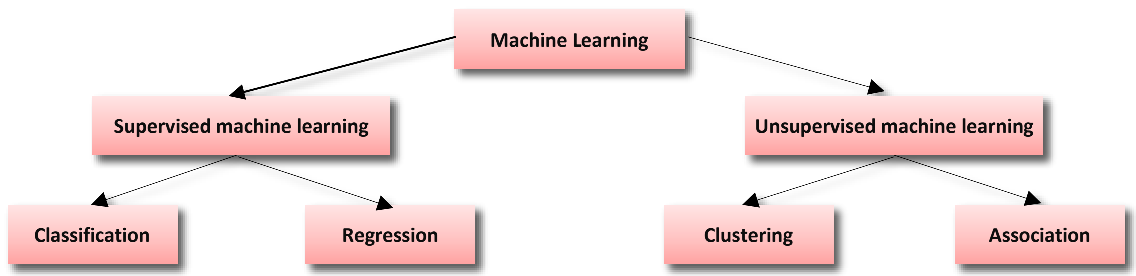
the availability of big data, and the growth of the learning algorithm efficiency [1].

Figure 1 shows the principal categorization of ML algorithms according to their main functionality. One can distinguish between Supervised Machine Learning (i.e. having an expert provide the so-called ground truth - the correct class or value - for each example in a dataset) and Unsupervised Machine Learning, where the objective is to find interesting patterns and frequent associations between examples in a dataset, without any human supervision (e.g. finding an automatic grouping of diseases by the similarity of symptoms).

Medical imaging applications mostly belong to the supervised ML category, because the correct interpretation (e.g. diagnosis, the classification of severity of a disease) of the result is provided by the medical experts who have analyzed it.

In the past decades, there was substantial growth in the healthcare applications one example is the deep learning algorithm that proved to have an outstanding accuracy in diabetic retinopathy identification [2].

Figure 1: Grouping the different types of machine learning algorithms according to the type of learning [3]



Yang et al [4] demonstrated the importance of AI about big data and parallel programming in medicine, especially in the field of cardiac imaging.

These last decades have also demonstrated the importance of medical imaging in the detection, diagnosis, and treatment of various conditions. In clinical applications, medical imaging is largely performed by a group of experts, such as cardiologists, radiologists, endocrinologists, and so on [5]. In this regard, the computer-assisted analysis enables a better interpretation of the medical image database available. Regarding the decoding of the parameters highlighted by the medical images, it is worth noticing the recent advances in deep learning techniques, which represent a considerable leap in the identification, classification, and quantification of medical conditions and/or health parameters based on input from different medical imaging techniques [6].

ARTIFICIAL INTELLIGENCE IN ECHOCARDIOGRAPHY

In the world of multimodal imaging in cardiology, echocardiography remains crucial for the diagnosis and management of patients with cardiovascular disease [7]. The advantages of the ultrasound of the heart compared to other imaging tools are low price, portability, the possibility of being repeated, short examination time, and the fact that the administration of contrast medium is unnecessary. However, errors in echocardiography quantification and conflict in the interpretation of echo images are frequent in everyday clinical practice.

Although it remains the main imagining modality used in cardiology, echocardiography has several shortcomings that can be improved. The echo machines have developed intensively during the last year (leading to accurate 2D and Doppler imaging and new technologies like tissue Doppler, speckle tracking, or 3D echocardiography). However, one of the main limitations of this method is high operator dependence. The learning curve in echocardiography is very steep and the knowledge, the experience, and sometimes even the mood of the echocardiographer are very important for the exam interpretation. For example, left ventricle ejection fraction is a crucial parameter for patient management but has a high inter- and intraobserver variability. Therefore, the result given by one observer can be different compared to another one or, even more, the same observer can give different interpretations when the reading is repeated. The purpose of AI is to overcome these issues.

Another important role of AI in this field is to solve the problem of a mismatch between the high number of echocardiography required in clinical practice and the number of cardiologists/echocardiographers available to interpret the studies. Moreover, a large volume of already acquired data is under-utilized during a routine echocardiogram and AI offers the possibility to interpret multiple datasets in a very short time [8].

The purpose of artificial intelligence in echocardiography is to detect the disease based on some specific echocardiographic criteria [9, 10]. AI can be used in the image-acquisition process as well and helps people with limited echocardiography training to obtain standard views by anatomic guidance.

Although the implication of AI in echocardiography is still less important compared to other imaging modalities, there are many examples of applications already being used.

Software algorithms are capable of correct identification of the ultrasound modality (2D, pulse wave Doppler or continuous wave Doppler) or the view (four-, two- or three-chamber view) [11]. Moreover, the identification of structures and even the quantification of some related parameters based on border detection are also possible. One of the first applications of AI in echocardiography was the assessment of left ventricular volumes and function initially based on 2D and subsequently on 3D [12]. Based on 3D echocardiography, the correct identification of the heart chamber borders offers results comparable to those measured by cardiac magnetic resonance (left ventricle volumes and function [13], right ventricle volumes, and function [14]. The new software can compute the chamber volumes not only at a maximum or minimum level but also dynamically through the cardiac cycle [15]. Some models for the automated diagnosis of regional wall motion abnormalities and myocardial infarction using deep learning algorithms are still developing [16].

AI is already aiding in valvular heart disease; there is automated software that offers the assessment of mitral [17] or aortic valve.

Some applications can already differentiate, with high sensitivity, between some pathological conditions that need an experienced human examination: left ventricular hypertrophy in athletic population vs. in hypertrophic cardiomyopathy [18], constrictive pericarditis vs. restrictive cardiomyopathy [19].

AI can change the way we read echocardiograms. Normally the interpretation of an echocardiogram is based on consecutive views analysis. For example, in aortic stenosis grading, the observer has to integrate information from multiple non-consecutive views (annulus diameter from the parasternal long axis, continuous wave and pulse wave Doppler data from apical 5 chamber or right parasternal). AI allows the classification of these images and the analysis of the ones related to aortic stenosis grading although they have not been acquired consecutively. Therefore, in the future, the reading of an echocardiogram will be based on the chamber or valve analysis in multiple views and not on the interpretation of consecutively acquired views.

A very important aspect is that using artificial intelligence in echocardiography can modify our understanding regarding the echocardiographic data. Our knowledge of echo interpretation is based on clinical trials that have included a target population. However, this population may not always be representative of the entire population. The large amount of data obtained by including artificial intelligence and machine learning in echocardiography can change our classifications, cut-offs, and interpretation of these data. For example, a recent study based on the NEDA registry (Australian New Zealand Clinical Trials registry) showed that patients with moderate aortic stenosis have similarly high rates of mortality compared to patients with severe aortic stenosis and, likely, we'll need to reevaluate our current data regarding the indications for intervention in aortic stenosis [20].

Therefore, in echocardiography, AI offers the possibility to interpret data from the real world and not from selected patients included in clinical trials and probably a better understanding of the diseases.

Recently, machine learning and deep learning have become the main direction of development in echocardiography, which is proved by the number of publications in PubMed [21]. The possible impact of artificial intelligence on echocardiography is impressive but for now, the human mind is still far too complex compared to AI [22].

Although we all dream of an automated program for echocardiogram interpretation, there is still a long journey ahead. Thus, cardiologists should have advanced knowledge and the capability to use artificial intelligence as extended intelligence.

ARTIFICIAL INTELLIGENCE IN CARDIAC MAGNETIC RESONANCE IMAGING

There is a concern among radiologists and medical students that AI will replace the radiologist. This is not likely to be the natural evolution, but radiologists who use artificial intelligence will replace those who do not or do not think they can use it.

The modern principles of medical imaging are based on the most efficient use of the techniques that bring the maximum amount of information in the shortest time possible, starting from the moment of clinical suspicion. This aspect makes it necessary for the clinician to know the value and the limits of each type of sectional imaging exploration, to optimize the indications of the examinations. Cardiac MRI has a very wide range of clinical applications and has been included in the guidelines for the assessment of congenital heart disease, heart tumors, pericardial disease, cardiac ventricular dysplasia, or myocardial ischemia - hibernating myocardium [23]. Other indications such as the evaluation of myocardial perfusion, ventricular or valvular function can be accurately evaluated by MRI, but compete with other imaging modalities, such as single-photon emission computed tomography (SPECT) and echocardiography, more commonly used in outpatient settings.

The major advantages of MRI are the absence of ionizing radiation and the very strong contrast and temporal resolutions (as opposed to CT, where the spatial resolution is very high [27]. Cardiac MRI provides a wealth of morphological and functional information about the heart. In some practices, the evaluation of the heart MRI requires a long global time, so the tendency is to standardize and reduce the time required for the exploration, but also for the analysis of the images obtained, by using the FAST MRI type techniques. To optimize these protocols for analyzing the data obtained from the scanning of the heart, AI techniques have been developed and used in clinical practice.

They are based on automatic machine learning techniques to enhance the ability to analyze images and data obtained by MRI scanning. The results are remarkable both in the optimization of scanning techniques and protocols, as well as in the analysis and integration of data and results. In an impressive achievement, the introduction of AI and the optimization through the machine learning algorithm can increase the speed of interpretation of the images obtained by cardiac MRI from an average of 13 minutes to about 4 seconds [24].

Cardiac MRI can establish the most appropriate plan for cardiac surgical planning, implantation of cardiac defibrillators, and assessment of cardiac toxicity in patients with oncological pathology. These decisions are based on the accuracy measurements made by MRI.

Multiple studies performed on significantly large numbers of patients have used the information to develop machine learning protocols [25]. These are based on neural network learning. For the time being, it is still necessary to validate the superiority of the efficient application of these AI-type protocols over the aspect of the presently considered examinations. At this moment, the cardiac MRI examinations intend to use a large database which, after a standardized examination and by using a minimum of subsequent maneuvers, the results will be offered in the form of measurements made automatically by the computer capable of filling an MRI result with multiple preformed fields. Also included in this result with preformed fields, the neural network algorithm also offers the diagnostic suspicions based on which differential diagnoses can be issued. The vision of those who work and create this advanced analysis and diagnostic software is to increase the speed of examination without sacrificing the accuracy and precision of interpretation.

The use of artificial intelligence is used to solve the following problems and challenges - the small number of radiologists, the long time required for each examination, the insufficient use of radiological equipment without corresponding efficiency [26].

Traditionally, CT and ultrasound are the most frequent techniques used for cardiac imaging examinations. However, MRI can occupy a very important place due to the very important contrast of tissue structures without ionizing radiation.

One of the major disadvantages of cardiac MRI is that the examination lasts for about an hour. For example, an existing software solution, called Heat Vista (available in the US), reduces the examination for suspected cardiac ischemia from 90 minutes to 15 minutes, and the solution is applied to existing equipment. The software recommends the protocol for about 10 seconds. All these technological advances also eliminate the need to examine through sequences with blocked breathing. This progress is achieved through sequences that recognize and detect artifacts and alert the technician if the sequence needs to be redone [28].

Another challenge is MRI examinations for patients with cardiac and vascular implants of various types of devices. It is necessary to adapt these protocols to the particular aspects of each patient and this aspect can be efficiently optimized by AI protocols depending on the type of implant and the manufacturer that produced them. Considering all the above, cardiac imaging and especially cardiac MRI will benefit from the integration of various AI solutions.

ARTIFICIAL INTELLIGENCE IN CARDIAC ANGIOGRAPHY

X-ray angiography is a medical imaging technique dedicated to the diagnosis and even treatment of vascular diseases. An angiography is obtained using an X-ray source and a detector located on both ends of a C-arm gantry. The imaging apparatus provides temporal images series for several seconds.

Table 1: Artificial Intelligence in cardiovascular medical imaging

Imaging Technique	Scope	Dataset	Approach Details	Measured Results
Cardiac MRI	Ventricle Segmentation [29]; Estimating Left Ventricle and Right Ventricle functioning	Cardiac MRI datasets, MICCAI 2012 RV segmentation challenge; 48 patients (16 training, 32 test)	Region of Interest (ROI) extraction using 960 cardiac MRI images with manually labeled RV and LV bounding boxes of size 150 x 150 px. Train CNNs for endocardium and epicardium semantic segmentation of RV on extracted bounding boxes.	Objective: contour overlap of segmented RV with ground truth Criteria: DM, HD, R, ME for EDV, ESV, and EF.
	Heart chamber segmentation [30]; Analyzing abnormality of wall motions	Cardiac MRI datasets, MICCAI 2012 RV segmentation challenge	Heart chamber ROI extraction using a deep learning approach for semantic segmentation. The segmentation approach was initialized with input from a prior edge detection algorithm.	Objective: contour overlap of segmented RV with ground truth Criteria: DM, HD, R, ME for EDV, ESV and EF.
Echocardiography	Regression task: left ventricular volume and ejection fraction computation; Decision making in valvular heart disease, heart failure and post-infarct care [31]	255 usable 2-dimensional echocardiography (2DE) studies	Local Ejection Fraction (EF) estimation. Comparative evaluation of automated EF measurements against manual inspection.	Objective: automated EF estimation Criteria: Intraclass correlation coefficients Bland-Altman analyses
	Regression task: left ventricular volume and Ejection Fraction estimation; [32]	218 patients including 165 with abnormal left ventricular (LV) function. 10,000 apical 4- and 2-chamber view images, from patients with cardiomyopathies, wall motion abnormalities, and dyssynchrony. Cardiac MRI for 21 patients	Identification of the Left Ventricle cavity. Manual tracing of the endocardial border. Left Ventricle volume estimation using modified Simpson's rule for Ejection Fraction computation.	Objective: automated EF estimation Criteria: 2-tailed Student t-test Bland-Altman analysis
Myocardial Perfusion Imaging (MPI) + Coronary angiography	Automatically predicting obstructive disease likelihood from myocardial perfusion imaging (MPI) [33]	1,638 patients without known coronary artery disease, undergoing stress 9mTc-sestamibi or tetrofosmin MPI in 9 different sites Coronary angiography performed within 6 months of MPI	Semantic segmentation of myocardium using a neural network method trained on raw and quantitative polar maps. Input for the network obtained using manual annotation of images obtained from nuclear cardiology software tools.	Objectives: obstructive disease prediction Criteria: area under the receiver-operating characteristic curve (AUC), sensitivity (SS)
SPECT+ computed tomography angiography	Estimating the likelihood of abnormality of coronary arteries in patients with ischemia [34]	1001 patients Coronary angiography within 60 days of myocardial perfusion SPECT for 59 patients with stable coronary artery disease	Semantic segmentation of artery zones with perfusion disorders. Use of segmentation to extract features such as shape, extent, location, count, perfusion homogeneity, regional motion, wall thickening, and sex	Objectives: obstructive disease prediction Criteria: SS, specificity, accuracy, AUC

DM – Dice metric, HD – Hausdorff distance, R – correlation coefficient, ME for EDV – mean errors for end-diastole volumes, ESV – end-systole volumes, EF – ejection fraction, MRI – magnetic resonance imaging

There are three types of angiograms: (i) monoplane angiography, which is the most common method and utilizes the single view principle, (ii) biplane angiography, which uses two C-arm systems for simultaneous acquiring of two different projections, and finally, (iii) rotational angiography, which can give the most accurate three-dimensional scenes by making a complete rotation around the patient.

In [33], the angiography and myocardial perfusion imaging are acquired from the same patient and used as training data on an artificial neural network (ANN) for an automatic prediction of obstructive disease. In [34], the coronary angiography is acquired within 60 days of myocardial perfusion SPECT for patients with stable coronary artery disease from a Japanese hospital. The purpose of ANN was to detect the coronary arteries responsible for the patients' cardiac ischemia. The algorithm accuracy to diagnose the culprit artery was similar to that of a medical expert.

Opportunities for AI applications at the peri-intervention stage are presented in [35] where diverse clinical investigations such as angiography, EKG, biomarkers are reunited for diagnosing STEMI patients. Some applications of machine learning techniques in angiography and other cardiac imaging methods can be found in Table 1.

CONCLUSIONS

The next challenge will be moving from focusing on technique and image analysis to tasks dedicated to physicians in the context of automation of other tasks. This may increase the time efficiency of the medical procedures, job satisfaction, better communication between patient-physician, and improvement of healthcare equality. AI-based solutions will contribute to fighting modern days' challenges, such as the decreasing number of skilled radiologists, leak of medical equipment used, and time-consuming diagnoses.

The final decision after integrating clinical data belongs to cardiologists. The role of artificial intelligence is not to replace humans but to make their work more accurate, fast, and efficient.

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References:

1. Spector L., "Evolution of artificial intelligence," Artificial Intelligence, vol. 170, no. 18, pp. 1251–1253, Dec. 2006.

2. Shen D., Wu G., Suk H., 2017. Deep Learning in Medical Image Analysis

3. Garbade M.J. 2018. Regression Versus Classification Machine Learning: What's the Difference?

4. Yang A., Troup M. 2017. Scalability and validation of big data bioinformatics software

5. Brody H. 2013. Medical imaging. Nature

6. Erickson B. J., Korfiatis P., Akkus Z., Kline T. L. 2017. Machine Learning for Medical Imaging

7. Alsharqi M., Woodward W.J., Mumith J.A., Markham D.C., Upton R., Leeson P. Artificial intelligence and echocardiography. Echo Res Pract. 2018 ;5(4): R115–R125.

8. Sengupta P.P., Huang Y.M., Bansal M., Ashrafi A., Fisher M., Shameer K., Gall W., Dudley J.T. Cognitive machine-learning algorithm for cardiac imaging: a pilot study for differentiating constrictive pericarditis from restrictive cardiomyopathy. Circulation: Cardiovascular Imaging. 2016; Jun;9(6). pii: e004330.

9. Kenya Kusunose, Akihiro Haga, Takashi Abe, Masataka Sata. Utilization of Artificial Intelligence in Echocardiography, Circulation Journal, 2019, Volume 83, Issue 8, Pages 1623-1629.

10. Zhang J., Gajjala S., Agrawal P. et al. Fully Automated Echocardiogram Interpretation in Clinical Practice. Circulation 2018; 138:1623-35.

11. Khamis H., Zurakhov G., Azar V., Raz A., Friedman Z., Adam D. Automatic apical view classification of echocardiograms using a discriminative learning dictionary. Medical Image Analysis 2017:36:15–21.

12. Cannesson M., Tanabe M., Suffoletto MS, McNamara D.M., Madan S., Lacomis J.M., Gorcsan. A novel two-dimensional echocardiographic image analysis system using artificial intelligence-learned pattern recognition for rapid automated ejection fraction. Journal of the American College of Cardiology 2007;49: 217–226.

13. Levy F., Dan Schouver E., Iacuzio L., Civaia F., Rusek S., Dommerc C., Marechaux S., Dor V, Tribouilloy C., Dreyfus G. Performance of new automated transthoracic three-dimensional echocardiographic software for left ventricular volumes and function assessment in routine clinical practice: Comparison with 3 Tesla cardiac magnetic resonance. Archives of Cardiovascular Diseases 2017:110:580–589.

14. Stebbing R.V., Namburete A.I., Upton R., Leeson P., Noble J.A. Data-driven shape parameterization for segmentation of the right ventricle from 3D echocardiography. Medical Image Analysis 2015;21: 29–39.

15. Tsang W., Salgo I.S., Medvedofsky D. et al. Transthoracic 3D Echocardiographic Left Heart Chamber Quantification Using an Automated Adaptive Analytics Algorithm. JACC Cardiovasc Imaging 2016; 9:769-82.

16. Kusunose K., Haga A., Abe T., Sata M. Utilization of Artificial Intelligence in Echocardiography. Circulation Journal 2019;83: 1623-1629.

17. Cobey F.C. Intelligent algorithms in perioperative echocardiography: a new era. Journal of the American Society of Echocardiography 2017;30: A26–A27

18. Narula S., Shameer K., Salem Omar A.M., Dudley J.T., Sengupta P.P. Machine-Learning Algorithms to Automate Morphological and Functional Assessments in 2D Echocardiography. J Am Coll Cardiol.

2016 Nov 29; 68(21):2287-2295.

19. Mahmoud A., Bansal M., Sengupta P.P. New Cardiac Imaging Algorithms to Diagnose Constrictive Pericarditis Versus Restrictive Cardiomyopathy. Curr Cardiol Rep. 2017 May; 19(5):43.

20. Strange G., Stewart S., Celermajer D. et al. Poor long-term survival in patients with moderate aortic stenosis. JACC imaging 2019, in press.

21. Sengupta P., Adjerh D. Will artificial Inteligence Replace the Human Echocardiographer? Circulation. 2018;138: 1639–1642.

22. Narang A., Lang R. Artificial intelligence and Echocardiography. Expert Analysis in ACC, 2019, 18 june.

23. Siegersma K.R., Leiner T., Chew D. P., Appelman Y., Hofstra L. & Verjans J. W. Artificial intelligence in cardiovascular imaging: state of the art and implications for the imaging cardiologist (2019)

24. Dey D., Slomka P.J., Leeson P., Comaniciu D., Shrestha S., Sengupta P.P., Marwick T.H. Artificial Intelligence in Cardiovascular Imaging: JACC State-of-the-Art Review Am Coll Cardiol. 2019.

25. Petersen, Abdulkareem M., Leiner T. Artificial Intelligence Will Transform Cardiac Imaging-Opportunities and Challenges. Front Cardiovasc Med. 2019 Sep 10;6: 133. doi:10.3389/fcvm.2019.00133. eCollection 2019

26. Thrall J.H., Li X., Li Q., Cruz C., Do S., Dreyer K., Brink J.J. Artificial Intelligence and Machine Learning in Radiology: Opportunities, Challenges, Pitfalls, and Criteria for Success. Am Coll Radiol 2018 Mar;15(3 Pt B):504-508.2017.12.026. Epub 2018 Feb 4.

27. Arsanjani R., Dey D., Khachatryan T. et al. Prediction of revascularization after myocardial perfusion SPECT by machine learning in a large population. J Nucl Cardiol. 2015; 22:877–884.

28. Avendi M.R., Kheradvar A., Jafarkhani H. A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI. Med Image Anal. 2016;30: 108–119.

29. G. Luo, R. An, K. Wang, S. Dong and H. Zhang, “A Deep Learning Network for Right Ventricle Segmentation in Short Axis MRI,” 2016 Computing in Cardiology Conference (Cin C), Sep. 2016.

30. M. Avendi, A. Kheradvar and H. Jafarkhani, “Fully automatic segmentation of heart chambers in cardiac MRI using deep learning,” Journal of Cardiovascular Magnetic Resonance, vol. 18, no. S1, Jan. 2016.

31. N. Furiasse and J. D. Thomas, “Automated Algorithmic Software in Echocardiography,” Journal of the American College of Cardiology, vol. 66, no. 13, pp. 1467–1469, Sep. 2015.

32. M. Cannesson, M. Tanabe, M. S. Suffoletto, D. M. McNamara, S. Madan, J. M. Lacomis and J. Gorcsan. “A Novel Two-Dimensional Echocardiographic Image Analysis System Using Artificial Intelligence-Learned Pattern Recognition for Rapid Automated Ejection Fraction,” Journal of the American College of Cardiology, vol. 49, no. 2, pp. 217–226, Jan. 2007.

33. J. Betancur, F. Commandeur, M. Motlagh, T. Sharir, A. J. Einstein, S. Bokhari, M. B. Fish, T. D. Ruddy, P. Kaufmann, A. J. Sinusas, E. J. Miller, T. M. Bateman, S. Dorbala, M. Di Carli, G. Germano, Y. Otaki, B. K. Tamarappoo, D. Dey, D. S. Berman, and P. J. Slomka, “Deep Learning for Prediction of Obstructive Disease From Fast Myocardial Perfusion SPECT,” JACC: Cardiovascular Imaging, vol. 11, no. 11, pp. 1654–1663, Nov. 2018.

34. H. Yoneyama, K. Nakajima, J. Taki, H. Wakabayashi, S. Matsuo, T. Konishi, K. Okuda, T. Shibutani, M. Onoguchi, and S. Kinuya, “Ability of artificial intelligence to diagnose coronary artery stenosis using hybrid images of coronary computed tomography angiography and myocardial perfusion SPECT,” European Journal of Hybrid Imaging, vol. 3, no. 1, Mar. 2019.

R.R. Bond, K. Rjoob, D. Finlay, V. Mc Gilligan S. J. Leslie, C. Knoery, A. Iftikhar, A. McShane, I.A. Tache, P. Biglarbeigi, M. Manktelow, A. Peace. Near future artificial intelligence in interventional cardiology: new opportunities and challenges to improve the care of STEMI patients. Digital Health Virtual Journal, 31 Mar 2020