OPINION ARTICLE

# Artificial Intelligence in Cardiac Imaging: the Future is Here

*Inteligencia artificial en imagen cardíaca: el futuro ya está aquí*

MIGUEL ÁNGEL GARCÍA FERNÁNDEZ[1]

The name artificial intelligence (AI) was coined during the conference organized by Marvin Minsky, John McCarthy and Claude Shanon in Dartmouth in 1956. This event can be considered the starting point of AI as a new scientific field. (1) We can define AI as "the activity generated by a machine that mimics the intellectual and knowledge functions that humans associate with human intelligence, such as reasoning, learning and solving problems."

In recent years, AI has presented spectacular potential for development, resulting in a revolution similar to the one generated by the industrial revolution in the 19th century. Artificial intelligence invades much of our daily activities; thus, Andrew Ng, expressing its future ubiquity, defines it as "the electricity of the 21st century." This author considers that there are three unstoppable areas of action for AI: computers with which we can talk, automatic cars without driver and the participation of AI in the area of health. There is no doubt that one of the most promising areas of AI progress is its application in the field of health in its many different aspects, including management and planning, reporting, information storage, diagnosis or its use in combination with Big Data that will allow the reclassification of many different pathologies in new subgroups. All these changes lead us to a future transformation of information and its use in the medical field, with the creation of a way of seeing, doing and managing that we could define as a "new form of medical knowledge and practice".

Within the applications of AI in the health area, one of the most promising is that of medical imaging, which has had spectacular growth in the last five years. A very graphic way to see the interest generated by the use of any progress in medicine is to follow a certain technique in PubMed publications. In 2005, 70 works of AI were published in medical imaging, 10 years later, the number amounted to almost 900 and we are currently around 2,500 publications. Recently, E. Topol analyzed the 10 technologies with the greatest impact and application in the health area in the coming years, and suggested that imaging diagnosis was the fourth most important advance in health technology changes in the near future. (2) The techniques involved are varied according to the specialty, but globally, cardiovascular magnetic resonance imaging (CMRI) and computed tomography (CT) lead this change, followed by ultrasound. Although neuroradiology and musculoskeletal system specialties were included first in AI research, more recently, cardiology has been incorporated with force with a brilliant future pathway.

The use of AI in medical imaging and, specifically, machine learning methods, can signify an increase in diagnostic capabilities and in the safety to obtain information on cardiac anatomy and function, modifying their future use in our daily practice. It is therefore important to know how to recognize the definition of each AI modality.

## ARTIFICIAL INTELLIGENCE: MACHINE LEARNING AND DEEP LEARNING

In AI, the machine learning field stocks the ability of the machine to learn, using large data sets with minimal supervision. Therefore, instead of fixed rules written in code, machine learning allows computers to learn on their own. A well-known example is Google's DeepMind, which managed to beat the go world champion, applying machine learning techniques and training with a large database that collected plays from experts in the game. This type of learning takes advantage of the calculating power of today's computers, which can easily process large data sets in a short time. A typical example of the use of machine learning is the detection of spam in email selection. We provide information of the emails we consider spam, and the computer learns to discriminate them.

An important leap was taken in 2010, in which the machine learns directly from the data, without any human supervision, a process we know as deep learning. Deep learning is based on the use of neural networks whose design resembles the human brain, more specifically, the use of the neural connections of the human retina. A neural network can learn from data, so that it can be trained to recognize patterns, classify data and predict future events.

In a simple way, a neural network groups neurons into different types of layers: input layer, hidden layers and output layers. Units connected to the external environment are

REV ARGENT CARDIOL 2019;87:469-473. http://dx.doi.org/10.7775/rac.v87.i6.16997

*Address for reprints:* Miguel Ángel García Fernández. c/Martínez Izquierdo 7Madrid - 28028, España. garciafernandez@ecocardio.

[1] Department of Cardiac Imaging, School of Medicine, Department of Medicine, Universidad Complutense de Madrid. España

designated as input units or input neural layer. There will also be an output neuronal layer that gives the response of the system. Other units (neurons) are simply connected to each other and have no direct relationship with the input or output information of the system, which is why they are called hidden units.

A simple example of how a neural network would work can be illustrated by calculating the price of a plane ticket. We can make a network with four neurons in the input layer, each dedicated to a specific question: city, company, date of reservation and flight class (tourist or executive). The input layers pass the information to the next layer or hidden layer, which performs a series of calculations and passes them to the next layers. Each connection between the neurons is associated with a data weight or "importance." In the example, more weight is given to the type of ticket than to the date of reservation; finally, the output layer gives us a prediction of prices. If we err, the machine keeps doing different tests to fit the best solution. A key point is to train the machine with real ticket prices, so that it takes references from reality.

There are three different types of neural networks, each with a different type of application: the deep neural network, which is basically used in text processing; the recurrent neural network, which is used in sequential data types; for example, the value of a company share, which will depend on the value of the previous day; and, finally, the convolutional neural network, which is the most used in imaging treatment. With the convolutional neural networks, the initial image is simplified by passing through a series of filters. Once the machine defines a calculation algorithm, a very important step is necessary, which is to test and rectify the algorithm automatically.

## ARTIFICIAL INTELLIGENCE IN CARDIAC MEDICAL IMAGING

Undoubtedly, one of the most promising areas among AI applications is its use in cardiac medical imaging. The applications are manifold comprising study planning, improvement of information storage, categorization of the importance and meaning of data, diagnosis of the disease, prognostic improvement based on personalized medicine, combination with genomic data and many other items. Whether we like it or not, the workflow is going to be modified in radiological or cardiac imaging areas involved in cardiology services. It is interesting to provide a hint of the changes that are coming in our work area as imaging experts.

## APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN CARDIAC COMPUTED TOMOGRAPHY

Computed tomography is increasingly incorporated into our clinical practice, especially with the performance of low radiation studies. The information provided by CT scan in coronary heart disease has many sources of action, ranging from the detection of pericardial fat or the analysis of the calcium score to the most sophisticated calculations of fractional coronary flow reserve (FFR). Artificial intelligence techniques have been incorporated into all scenarios in which CT scan can play a diagnostic role in coronary heart disease. Thus, the calcium score is a definitely useful parameter for a better assessment of coronary risk. Using the cases included in the well-known CONFIRM study, Al'Aref et al. recently analyzed different predictive models of coronary heart disease with machine learning, and compared them with the classical model of clinical variables. (3) The conclusion was that the model obtained with machine learning and calcium scoring achieved the best accuracy and was superior to the rest of the models analyzed.

The assessment of obstructive lesion severity is one of the CT challenges. Kang (4) demonstrates for the first time that using support vector machine algorithms it is possible to determine the severity of the lesion with high sensitivity (93%) and specificity (95%). Similarly, it has been confirmed that the complicated computer calculations to obtain FFR with CT scan can be approached in a simpler way with the use of AI. (5, 6) Finally, it has recently been proven that automatic quantification of thoracic and epicardial adipose tissue is possible with the use of deep learning, with excellent correlations with the segmentation performed by the expert. (7)

## APPLICATIONS IN CARDIOVASCULAR MAGNETIC RESONANCE IMAGING

One of the aspects to which more work has been devoted in the world of CMRI is the achievement of image segmentation mechanisms that allow us to automatically and quickly calculate ventricular function. Only four years ago, the NIH challenged cardiac imaging experts to look for algorithms to reliably calculate LV volumes and ejection fraction using AI. Only two years later, the FDA gave its approval to these automatic calculation methods. Very recently, a multicenter analysis with different machines confirmed that the measurements of ventricular function with machine learning have an accuracy similar to those performed by humans with the most exquisite and refined techniques. (8) The most striking aspect of this work is that the measurement of ventricular function took the machine 0.007 minutes, which implies that it was 186 times faster (!) than the human assessment.

The calculation of right ventricular function is another of the great challenges of imaging techniques, and there is sufficient information to define the usefulness of the AI technique in the segmentation of the right ventricle and in the measurement of parameters associated to its function. (9)

## ECHOCARDIOGRAPHY AND ARTIFICIAL INTELLIGENCE

Echocardiography is undoubtedly the most widely used diagnostic technique in the field of cardiology. The application of AI completes some of its limitations and opens fields aimed at a more efficient use of echocardiography. The starting point for an evaluation and analysis of the echocardiogram with AI is to teach it in what mode and plane we are working. Thus, Kamis et al. (10) and Madani et al. (11) confirm that using machine learning and deep learning algorithms, 95% -98% of the sections obtained can be accurately recognized.

A basic aspect in echocardiography is quantification, a field in which the use of AI is taking gigantic steps. Using random forest algorithms, the Chicago group of R. Lang (12,

13) has demonstrated its ability to accurately obtain endocardial borders and, therefore, calculate chamber volumes, with values comparable to the gold standard, CMRI. In this sense, the whole development of the "heart model", initiated by this working group, has actually been the first incorporation of AI into ultrasound machines and its use in our daily practice. On the other hand, there are new algorithms that allow the measurement of complex parameters such as the automatic calculation of the three-dimensional proximal isovelocity surface area (PISA) (14), the three-dimensional measurement of the mitral valve (15), or spatial patterns of aortic root and aortic valve recognition (16), which again achieve more precision and higher calculation speed. Very recently, Asch et al. (17) confirmed that even ejection fraction quantification with machine learning without the use of endocardial borders (a sort of computer "eye ball", and therefore, without direct volume measurement) yields similar values, comparable to those obtained by a panel of experts with traditional methods.

The final aim of these AI techniques is to be able to establish a definitive image-based diagnosis in different situations in which it is difficult to perform and requires great expertise from the operator to accomplish it. A typical example of this is to distinguish between the athlete physiological or pathological hypertrophy. Effectively, AI with artificial neural networks and random forest algorithms has been reported to establish the differential diagnosis between these two entities with sensitivity greater than 95% (18). Recently, Omar et al. (19) have shown that convolutional networks can be used to increase the diagnostic safety of stress echocardiography. Also, Sengupta et al. (20) have confirmed the usefulness of a machine learning algorithm to identify constrictive pericarditis from restrictive cardiomyopathy, with a diagnostic safety of 90%. Similarly, Zhang carried out a diagnostic training of convolutional neural networks on a set of about 14,000 studies and demonstrated that they are accurate for the diagnosis of pulmonary arterial hypertension, amyloidosis and hypertrophic cardiomyopathy. (20)

I have no doubt that in the very near future, the expert who sits down to review an echocardiography study will encounter, in a first step and before assessing the study, all the measurements reported and analyzed by the machine with AI, including the calculations obtained by 3D, which will then definitively be part of our routine. This surprising scenario with machines that work tirelessly will mean greater safety in the measurements and a decrease in the variability between observers, avoiding possible differences between the assessments that arise when the study is carried out by a non-expert. There will be less waste of time in the analysis of routine data and more time available to do what humans do best, which is to compare, associate and interrelate diagnostic concepts between all the possible paths to study a patient, including imaging technical data, clinical history, ECG and exploration.

## APPLICATIONS IN NUCLEAR MEDICINE STUDIES

Studies with nuclear medicine for the assessment of ischemic heart disease have also been analyzed with AI techniques, as reported by the abundant information in the literature. In this regard, it is worth highlighting the findings of Betancur et al., who showed that machine learning techniques for the evaluation of myocardial perfusion exhibited a diagnostic safety similar to that obtained by two experts. (21, 22) Similarly, Arsanjani et al. (23) demonstrated that the machine learning technique predicts early revascularization with great reliability after single photon emission computed tomography (SPECT), and that, combined with quantitative perfusion data and clinical data, significantly improves the technique's diagnostic performance. Similarly, AI techniques also increase the prognostic value of functional alterations registered by PET-CT methods. (24)

## RADIOMICS AND CARDIAC IMAGING

A very important field in the world of AI is radiomics (25), defined as the analysis of the measurable and quantifiable information contained in radiographic images such as CT scan or CMRI that are not detectable by the human eye. Its application has opened a world in precision medicine, mainly in medical oncology, to improve patient diagnosis and prognosis (26, 27). Until now, its application in the world of cardiac imaging had been very limited. Recently, Cetim et al. (27) opened a really exciting path by studying changes in the texture of the myocardial image in hypertensive patients, which cannot be demonstrated with the classical study of myocardial anatomy and function with CMRI. The authors analyze with AI about 700 (¡) data of each CMRI image, ranging from the classic measures of gray-scale distribution and their spatial relationships to statistically very complex analyses of myocardial textures. Surprisingly, the authors confirm their hypothesis that using radiomics analysis with CMRI it is possible to identify early myocardial involvement in hypertensive patients long before classic structural abnormalities, and thus create new disease phenotypes. This study opens an exciting scenario, allowing patient reclassification in a host of pathologies such as hypertrophy, amyloidosis, coronary heart disease, diabetes and many more thanks to the study of myocardial radiomics by using AI.

But the concepts of radiomics can also be applied to echocardiography (why no Echomics?) Effectively, beyond the naked eye image interpretation, there are the changes produced in myocardial deformation using the echocardiographic analysis of myocardial strain with speckle tracking. Experimental studies have shown that initial changes in strain are produced by abnormal calcium homeostasis, so it has been postulated that an echocardiographic "digital biopsy" could be performed with its study. (29) The sum of echocardiographic information (including myocardial strain) with laboratory data and clinical data using machine learning would enable reclassification of patients with heart failure and preserved ejection fraction into different phenotype groups. These studies open a new field in patient reclassification, which could have important therapeutic consequences and be extended to other pathologies.

## WHERE WE ARE GOING WITH THE USE OF ARTIFICIAL INTELLIGENCE IN CARDIOVASCULAR IMAGING

When talking about AI, specifically in diagnostic imaging techniques, the question always arises as to whether imaging experts are a medical “lineage” ready to disappear with the appearance of machines that diagnose with more precision than us. Undoubtedly, the way we work in our setting will change as AI becomes incorporated into our routine. Let us think that we are at the dawn of the method, something like the M mode of AI, and that the field of development is immense. However, in my opinion we should not worry about the possibility of our displacement; on the contrary, we must welcome this tool, which will help the human brain to be more effective. We must remember that our brain has innate abilities of abstraction, reasoning, common sense and integration of knowledge, and one of the great virtues of the association of our billions of neurons is to be able to establish patterns with hierarchical levels of knowledge based on our previous experience, which are impossible to carry out with the simplicity of the artificial neural networks that a computer manages.

To believe that the machines we create are going to replace us is to have little confidence in the brains that created them. On the contrary, the machines must free us from work that complicates our routine, as other machines throughout history (from the washing machine to the field collection machines) have freed us from tedious work. These machines will make us more effective, with more resolution capacity, with elimination of complicated calculations and wasted time, with accurate measurements, so that the variable “expert or non-expert” will be eradicated. We will have more time to devote to that in which we really outweigh the machines: our ability to abstract ourselves, to associate ideas, to integrate and interrelate knowledge and concepts, appealing to common sense. Finally, we will have more time to communicate with the patient, the center of our profession.

We are in the infancy of the method and must wait for the refinements in its use to define its place in the daily clinic, although its first babblings promise a spectacular future.

## REFERENCES

**1.** Kaplan A, Haenlein M. Siri, Siri, in my hand: Who’s the fairest in the land? On the interpretations, illustrations, and implications of AI. Bus Horiz 2019;62:15-25. http://doi.org/gf443d

**2.** Topol E. High-performance medicine: the convergence of human and AI. Nat Med 2019;25:44-56. http://doi.org/gfsvzn

**3.** Al’Aref SJ, Maliakal G, Singh G, van Rosendael AR, Ma X, Xu Z, et al. Machine learning of clinical variables and coronary artery calcium scoring for the prediction of obstructive coronary artery disease on coronary computed tomography angiography: analysis from the CONFIRM registry Eur Heart J 2019 pii:ehz565. http://doi.org/df68

**4.** Kang D, Dey D, Slomka PJ, Arsanjani R, Nakazato R, Ko H, et al. Structured learning algorithm for detection of nonobstructive and obstructive coronary plaque lesions from computed tomography angiography. J Med Imaging (Bellingham). 2015;2:014003. http://doi.org/df69

**5.** Tesche C, De Cecco CN, Albrecht MH, Duguay TM, Bayer RR, Litwin SE, et al. Coronary CT angiography-derived fractional flow reserve. Radiology 2017;285:17-33. http://doi.org/gbz8hn

**6.** Duguay TM, Tesche C, Vliegenthart R, De Cecco CN, Lin H, Albrecht MH, et al. Coronary computed tomographic angiography-. derived fractional flow reserve based on machine learning for risk stratification of non-culprit coronary narrowing in Patients with Acute Coronary Syndrome. Am J Cardiol. 2017;120:1260-6. http://doi.org/gchvwt

**7.** Commandeur F, Goeller M, Betancur J, Cadet S, Doris M, Chen X, et al. Deep Learning for Quantification of Epicardial and Thoracic Adipose Tissue From Non-Contrast CT. IEEE Trans Med Imaging. 2018;37:1835-46. http://doi.org/df7b.

**8.** A Multicenter, Scan-Rescan, Human and Machine Learning CMR Study to Test Generalizability and Precision in Imaging Biomarker Analysis. Circ Cardiovasc Imaging. 2019;12:e009214. http://doi.org/df8q

**9.** Medvedofsky D, Addetia K, Hamilton J, Leon Jimenez J, Lang RM, Mor-Avi V. Semi-automated echocardiographic quantification of right ventricular size and function. Int J Cardiovasc Imaging. 2015;31:1149-57.
http://doi.org/df7c.

**10.** Khamis H, Zurakhov G, Azar V, Raz A, Friedman Z, Adam D. Automatic apical view classification of echocardiograms using a discriminative learning dictionary. Med Image Anal. 2017;36:15-21. http://doi.org/f9qn5r

**11.** Madani A, Arnaout R, Mofrad M, Arnaout R. Fast and accurate view classification of echocardiograms using deep learning. NPJ Digit Med. 2018;6:1-8. http://doi.org/gc6x52

**12.** Otani K, Nakazono A, Salgo IS, Lang RM, Takeuchi M. Three-dimensional echocardiographic assessment of left heart chamber size and function with fully automated quantification software in patients with atrial fibrillation. J Am Soc Echocardiogr 2016;29:955-65. http://doi.org/f874ck

**13.** Tamborini G, Piazzese C, Lang RM, Muratori M, Chiorino E, Mapelli M, et al. Feasibility and Accuracy of Automated Software for Transthoracic Three-Dimensional Left Ventricular Volume and Function Analysis: Comparisons with Two-Dimensional Echocardiography, Three-Dimensional Transthoracic Manual Method, and Cardiac Magnetic Resonance Imaging. J Am Soc Echocardiogr. 2017;30:1049-58. http://doi.org/gcj3wz

**14.** de Agustín JA, Marcos-Alberca P, Fernandez-Golfin C, Gonçalves A, Feltes G, Nuñez-Gil IJ, et al. Direct measurement of proximal isovelocity surface area by single-beat three-dimensional color Doppler echocardiography in mitral regurgitation: a validation study. J Am Soc Echocardiogr. 2012;25:815-23. http://doi.org/q2s

**15.** Kagiyama N, Toki M, Hara M, Fukuda S, Aritaka S, Miki T, et al. Efficacy and Accuracy of Novel Automated Mitral Valve Quantification: Three-Dimensional Transesophageal Echocardiographic Study. Echocardiography. 2016;33:756-63. http://doi.org/df8r

**16.** Calleja A, Thavendiranathan P, Ionasec RI, Houle H, Liu S, Voigt I, et al. Automated quantitative 3-dimensional modeling of the aortic valve and root by 3-dimensional transesophageal echocardiography in normals, aortic regurgitation, and aortic stenosis: comparison to computed tomography in normals and clinical implications. Circ Cardiovasc Imaging. 2013;6:99-108. http://doi.org/df8s

**17.** Asch FM, Poilvert N, Abraham T, Jankowski M, Cleve J, Adams M, et al. Automated echocardiographic quantification of left ventricular ejection fraction without volume measurements using a machine learning algorithm mimicking a human expert. Circ Cardiovasc Imaging. 2019;12:e009303. http://doi.org/df8t

**18.** Narula S, Shameer K, Salem Omar AM, Dudley JT, Sengupta PP. Machine-Learning Algorithms to Automate Morphological and Functional Assessments in 2D Echocardiography. J Am Coll Cardiol. 2016;68:2287-95. http://doi.org/f9d23v

**19.** Omar HA, Domingos JS, Patra A, Upton R, Leeson P, Noble JA. Quantification of cardiac bull’s-eye map based on principal strain analysis for myocardial wall motion assessment in stress echocardiography. In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), 2018. http://doi.org/df8v

**20.** Sengupta PP, Huang YM, Bansal M, Ashrafi A, Fisher M, Shameer K, et al. Cognitive Machine-Learning Algorithm for Cardiac Imaging: A Pilot Study for Differentiating Constrictive Pericarditis From Restrictive Cardiomyopathy. Circ Cardiovasc Imaging. 2016;9. pii: e004330. http://doi.org/df8w

**21.** Betancur J, Rubeaux M, Fuchs TA, Otaki Y, Arnson Y, Slipczuk L, et al. Automatic valve plane localization in myocardial perfusion SPECT/CT by machine learning: anatomic and clinical validation. J Nucl Med 2017;58:961–7. http://doi.org/gbhnpv

**22.** Betancur J, Commandeur F, Motlagh M, Sharir T, Einstein AJ, Bokhari S, et al. Deep Learning for Prediction of Obstructive Disease From Fast Myocardial Perfusion SPECT: A Multicenter Study. JACC Cardiovasc Imaging. 2018;11:1654-63. http://doi.org/df8x

**23.** Arsanjani R, Xu Y, Hayes SW, Fish M, Lemley M Jr, Gerlach J, et al. Comparison of fully automated computer analysis and visual scoring for detection of coronary artery disease from myocardial perfusion SPECT in a large population. J Nucl Med 2013;54:221–8. http://doi.org/f4pc6s

**24.** Arsanjani R, Xu Y, Dey D, Fish M, Dorbala S, Hayes S, et al. Improved accuracy of myocardial perfusion SPECT for the detection of coronary artery disease using a support vector machine algorithm. J Nucl Med 2013;54:549-55. http://doi.org/f4s9rc

**25.** Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images Are More than Pictures, They Are Data. Radiology 2016;278:563-77. http://doi.org/f8rzch

**26.** Aerts HJ, Velazquez ER, Leijenaar RT, Parmar C, Grossmann P, Carvalho S, et al. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat Commun. 2014;5:4006. http://doi.org/f59qdv

**27.** Arimura H, Soufi M. A review on radiomics for personalized medicine in cancer treatment. Med Imaging Technol 2018;36:81-9.

**28.** Cetim I, Petersen SE, Napel S, Camara O, González Ballester MA, Lekadir K. A radiomics approach to analyze cardiac alterations in hypertension 019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) April 8-11, 2019 http://doi.org/df8z

**29.** Shah SJ. 20th Annual Feigenbaum Lecture: Echocardiography for Precision Medicine-Digital Biopsy to Deconstruct Biology. J Am Soc Echocardiogr 2019; 32:1379-95. http://doi.org/dg2d