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Review Article

Integration of Machine Learning into the Field of Cardiac Imaging

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Abstract

Machine learning (ML) has changed an essential aspect of human life. This is a subdivision of Artificial intelligence where the machines automatically extract valuable information by the databases' patterns. It has been widely used in medical science, and particularly within the area of computational cardiology. Here, in this chapter, we present a brief picture of a machine-learning algorithm that is used for predictive data-driven models. We also emphasize various domains of machine learning application, such as non-invasive imaging modalities. We bring to a close-by reviewing the drawbacks associated with the current application of Machine learning algorithms within computational cardiology.

Keywords: Computational Cardiology; Artificial Intelligence; Medical Imaging; Machine learning; Medical Science

Introduction

The researchers are learning and becoming experts using machine learning (ML) techniques to analyze cardiovascular imaging. ML has been beneficial in analyzing and identifying lesions from medical images with various applications such as supervised or unsupervised ML and ML algorithms such as deep neural network and cluster analysis. Though manual segmentation of medical images provides high accuracy, ML analysis may offer a fast breakdown of images with desirable or even higher accuracy. Automation techniques to read and interpret medical images can save millions of dollars, and patient can be benefitted from diagnostic test results in minutes. It can avoid unnecessary anxiety to wait for negative results or it can aid in fast management for abnormal results.

The principles of ML have already been applied on echocardiography, Cardiac MRI, and CT scan images. Madani., *et al.* has performed ML analysis on the thousands of echocardiography images data, divide them into training and a test set and compares the final results with a reading of board-certified echocardiographers. The results were 91.7% accurate [1]. Another study was performed to calculate the Agatston score from non-enhanced chest CT without prior segmentation of coronary artery calcification by González., *et al.* and achieved a Pearson coefficient of 0.923 [2].

Here, our goal is to understand the machine learning algorithm in the development clinical studies, how machine learning is essential in cardiac imaging, and the selection of the suitable algorithm implementation in cardiac imaging.

Ngo., *et al*. has performed a study for segmentation of cardiac left ventricular wall from cine magnetic resonance imaging and assessed a cardiac function. The results outperformed manual segmentation [3].

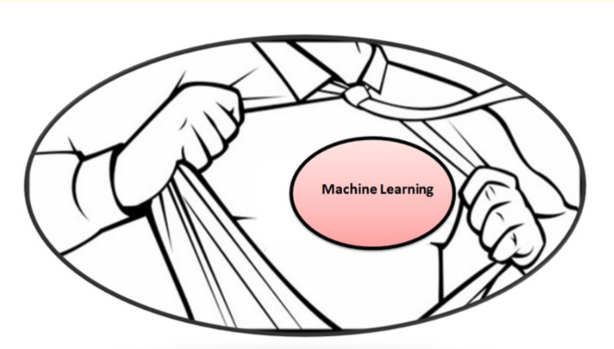

Figure 1: Machine learning in the cardiology.

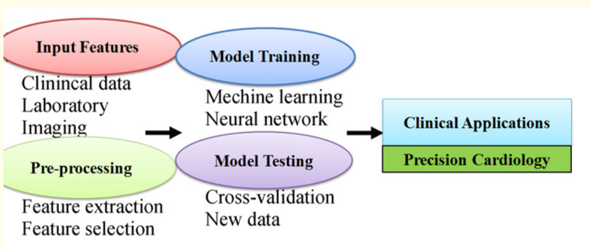

Figure 2: Schematic flow of a common machine learning algorithm development in clinical studies.

Imaging modalities for cardiac imaging

Chest X-ray (CXR) modality is the first non-invasive imaging techniques for the patient with suspected cases of heart or any kind of disease where X-ray radiation is used to depict the chest in creating a stationary projection image on the detector [22]. These imaging techniques provide structural information, size, the shape of the heart and the other part of information such as lungs and bones. Though, it doesn't work for the internal heart structure information because of the loss of depth information. So, cardiovascular disease cannot be diagnosed accurately based on the Chest X-ray.

The next imaging modality is the Angiography that utilizes X-ray radiation to image the heart. These techniques need the radio contrast agent injection into the blood, and a small amount of the X-ray beam is used to produce real-time images of the heart based on the fluoroscopy. In coronary artery disease, this technique can be used to recognize the infarct region. Additionally, this imaging process is used for cardiac resynchronization therapy for the patient who does have heart failure [23-25]. This imaging procedure is also very important for guiding the clinicians during the cardiac electrophysiology process for the patients who do have cardiac arrhythmias [26-28]. Though, this technique is contraindicated for patients who are allergic to radio contrast agents. It also does not work for pregnant women and children because of the risk of radiation. Myocardial perfusion imaging is another non-invasive type of heart assessment that uses nuclear medicine imaging techniques. In this imaging procedure, a small quantity of radiotracer has to inject into the blood, inhaled or swallowed. The radiotracer travels to the particular target area and emits gamma rays, which detected by a gamma camera and computer to process the images of the examined structure. This technique provides information about blood flow and coronary artery disease [29]. There are two approaches for MPI which is single-photon emission computed tomography (SPECT) and positron emission tomography (PET). Cardiac Computer Tomography (CT) is a non-invasive test that uses X-rays to take pictures of the heart. Now a day, Advance CT scanners (multidetector CT, or MDCT) work very fast and with a detailed description. They can also take images of the beating heart, and exhibit the calcium and blockages in the heart arteries [30-32].

MRI inspection utilizes a very strong magnetic field to make maps of atomic nuclei (H atoms in the water or fat molecules in the whole body). The process capturing the preliminary sequence of exciting pulses and recording of the emitted sign acquires the relevant images. The maps for a cardiac structure are generated with the use of amplitude of the signal. MRI produces images with high resolution as well as high tissue contrast useful for the assessment of heart chambers heart valves size and blood flow through the major vessels, and surrounding structures such as the pericardium. MRI is also utilized in diagnosing a variety of cardiovascular disorders such as tumors and inflammatory conditions [33-35].

Echocardiography or an ultrasound (US) imaging of the heart is widely used cardiac imaging techniques. The basic principle of echocardiography contains the generation of high-frequency sound waves, directed towards the tissue. An amount of the sound waves that inserts the tissue are reflected toward the transducer when the waves encounter the tissues with various reflective indices. The reflected signals are evaluated and processed by the echocardiography system to reconstruct images of the heart structures. Nowadays, two-dimensional echocardiography is the major preoperative imaging modality for cardiac disease diagnosis [36,37].

Machine learning-usefulness and challenges in cardiac imaging

Automation with ML techniques on medical images does have the potential to detect a subclinical disease from medical images, change disease management and improve clinical outcomes down the road in the future. Cardiac Ultrasound is the most widely and frequently used diagnostic tool for many cardiac diseases. Speckle tracking echocardiography (SPE) technique identifies the endocardial border. Segmentation of echocardiography images along with speckle tracking is commonly used and very useful approach to identify structural and functional abnormality of the myocardial wall. The extracted features and data from images can be feed in machine learning algorithms to detect and differentiate between physiological versus pathological abnormality. However, the segmentation technique of pixel-based classification of a structure can be very challenging when the boundaries are missing or when ultrasound data is of poor quality [4]. ML analysis of combining clinical variable data with echocardiography images can also, provide the bulk of clinically useful information as well as help to identify unrecognized associations between risk factors and relevant cardiac diseases.

There are several other advantages with ML when applied to echocardiography images. 1) Decrease inter-observer variability 2) consistent and reproducible results 3) rapid and accurate analysis with decrease need for unnecessary testing, thus reducing healthcare cost 4) identify hidden patterns and/or subclinical disease 5) aid clinicians in decision making for disease management [10]. ML models have also shown promising a role for enhancing sensitivity and specificity of stress echocardiography for identifying cardiac wall motion abnormalities. The other area of interest is assessment of the mitral valve annulus size and its morphology, classifying arrhythmia, amyloidosis and hypertrophic cardiomyopathy as well as aortic valve segmentation for planning transthoracic aortic valve implantation procedure [11].

There are several challenges come across when we try to apply the principals of machine learning while performing techniques of computational modeling on cardiac images. First of all, the interpretation of medical images requires intense training and experience. Medical images are difficult to label, as it needs expertise and also there is a need to filter out irrelevant information which itself is a time-consuming process. Echocardiography data contain still images as well as videos. The beat-to-beat variability in cardiac performance and presentation of a 3-D object to the 2-D image of ultrasound add more complexity for measurement. In addition, currently used ML algorithms are of limited help to analyze high-resolution images [5,6]. Furthermore, ML model developed to predict or to test needs ongoing and frequent validation of a diagnostic test before it can be used as a routine cardiology practice. ML analysis and automation can assist imaging readers to expedite the review of thousands of images captured with different modalities on a daily basis [7-9].

Types of machine learning

1. Supervised Learning: Learning from experience
2. Unsupervised Learning: Learning from a pattern
3. Re-enforcement Learning: Learning from reward
4. Semi-supervised Learning: Mixture of supervised and unsupervised learning
5. Transduction: Predict specific by learning specific items in the domain.

The majority of ML applications used on medical imaging involved supervised learning. First, in supervised learning, the training dataset is labeled and the machine is trained to correctly classify the data. Once the ML algorithms identify and learn patterns within a data, and then it compares them with known outcomes during the training phase. After that, its ability to identify similar patterns can be tested on a test dataset to validate and assess accuracy of the model compare to human interpretation [11]. In deep learning, a convolutional neural network (CNN, or Conv Net) is a class of deep neural networks that contains a convolutional part where hierarchical feature extraction arises and a fully connected part for classification or depending on the nature of the output. Deep learning, a branch of ML principals can also be applied for image classification, quantification of structure and function, segmentations and disease identification. Implementation of Deep learning on the cardiac images has been also an active subject of the research in the last few years like classification of the abnor-

Algorithm	Suitability	Advantage	Disadvantage
Support Vector Machines	Character recognition Image recognition	Automatic nonlinear feature creation Complex nonlinear functions	It is very difficult to explain when applying nonlinear kernels Hard to train after 10,000 examples as it takes long time
Random Forest	Almost every machine learning problem and Bioinformatics field.	Rarely overfits Automatically handles missing values There is no need to transform any variable There is no need to tweak parameters It can be utilized by almost everyone with great results can be achieved	Very difficult to interpret Weaker on regression when estimating values at the extremities of the distribution of response values Biased in multiclass problems toward more frequent classes
Neural Networks	Image recognition Language recognition and translation	Robust to outliers It works only with a portion of the examples (the support vectors)	Very difficult to set up Difficult to tune due to the fact of numerous parameters and hard to decide the structure of the network hard to interpret Easy to overfit
Naive Bayes	Face recognition Text classification	Easy to implement, It doesn't require too much memory Easy to understand Considers prior knowledge	Strong feature independence assumptions Fails to estimate rare occurrences Suffers from irrelevant features
Linear regression	Baseline predictions Econometric predictions Modelling marketing responses	Simple to understand It seldom overfits Fast and easy to train	To make it fit nonlinear functions Can suffer from outliers

Logistic regression	Ordering results by probability Modeling marketing responses	Simple to understand and explain Using L1 and L2 regularization is effective in feature selection The best algorithm for predicting probabilities of an event Fast to train	To make it fit nonlinear functions Can suffer from outliers
Adaboost	Face detection	Automatically handles missing values It doesn't overfit easily It can leverage many different weak-learners	Sensitive to noisy data and outliers
K-means	Segmentation	Fast in finding clusters Can detect outliers in multiple dimensions	Can't detect groups of other shape Unstable solutions, depends on initialization
K-nearest Neighbors	Computer vision Multilabel tagging	Fast, lazy training Can naturally handle extreme multiclass problems	Slow and cumbersome in the predicting phase Can fail to predict correctly due to the curse of dimensionality
Gradient Boosting	Almost any machine-learning problem	It can approximate most nonlinear function Best in class predictor	It can overfit if run for too many iterations Sensitive to noisy data and outliers
PCA	Removing co-linearity Reducing dimensions of the dataset	Can reduce data dimensionality	Implies strong linear assumptions (components are a weighted summations of features)

Table 1: Description about the algorithm, which is frequently used in the machine learning.

mal tissue on the CT scans [12,13], detection of the nodules on CT images [14,15]. Some of the radiologists highlight the significance of remaining optimistic about the upcoming opportunities of machine learning the revolution. It is a very essential for medical science to devote in the understanding of this innovative technology for the upcoming future.

An image registration technique for the heart disease diagnosis

Medical imaging plays a very significant role in the treatment of cardiovascular disease. There are various imaging modalities that can help to diagnose the heart disease such as single-photon emission computed tomography, echocardiography, X-ray, positron emission tomography (PET), Computer tomography (CT), and magnetic resonance imaging (MRI). Each imaging modalities provides very unique information and overcomes very specific challenges in cardiac imaging.

Usually, doctors prescribe more than one imaging method to collect more information about the heart condition before making any diagnosis decision. Imaging modalities also play a major role in Interventional cardiac diagnosis. Numerous imaging modalities like echocardiography and angiography are regularly used during the interventional procedures to provide a visual aid to the clinicians.

In very particular clinical cases, various images are acquired at different time points. Images can also be taken along with different imaging modalities. Hence, image fusion is valuable for the integration of diverse sources of information. It involves an initial process of image registration. In the field of biomedical research, image registration has become a very popular approach. In 1992, Brown research group has shown a broad survey on various registration methods [16]. And other various research groups reviewed the state-of-the-art registration algorithms and cardiac image registration [17-21]. Multimodality image registration of the cardiac structure is a very complex process relative to the other body part such as brain or kidney, due to the deformable nature of the heart. In this section, we aim to provide a basic framework on image registration research performed using a number of imaging modalities, and implementation tactics of the image registration.

Implementation Strategy for cardiac image registration

Spatial Transformation	Interpolation	Similarity Measures	Optimization
Rigidity Rigid • Basic: Translation and rotation • Affine: Translation, rotation, scaling. Nonrigid • Thin-plate splines • Polynomial terms • B-splines • Pseudophysical model **Dimensionality** 2D to 2D 3D to 3D 2D to 3D	Intensity-based Object-based	Intensity difference and correlation Mutual information and normalized mutual information	Generic Algorithm Gradient descent Levenberg- Marquardt Multiresolution

Table 2: Various methods of implementation approach for cardiac image registration.

Challenges and future directions

Artificial intelligence in the computational cardiology has grown greatly in the few years and their growth potential is very huge. Though, this development brings with it the need to overcome various challenges, such as ethical limitations, expansion of mathematical information, extraction of the health data, improvement of security, need for collaboration, and data-based care. The main idea is to present better support for the decision-making, including improved performance. This is data-driven care management with a high dynamism, which will encourage a greater personalization of care, and a real-time estimation of the experience of the health system users, intending at generating value for the patient. In this framework, the mechanical tasks will be substitutable and a variety of new tasks will be included in the routine of the cardiologist of precision, from the sufficient construction of the databases to the critical reflection on the results obtained by the mathematical-computational models, as well as the development of an enough physician-patient-data relationship.

Conclusion

AI has been revealed to be an essential way for the clinical practice of present cardiology. Numerous applications have been successfully performed, and have agreed on major improvements from a diagnostic and therapeutic point of view and in relation to personalized care. It is imperative that health data be used, which certainly involves a new design in the modus operandi of various health services. The nature of these data is varied and involves new sources, such as wearable devices and omic-data. Yet, this novel digital ecosystem needs the extraction of knowledge not traditionally found in regular medical courses. Therefore, a curricular redesign is to need and ought to be the object of a profound debate and particular actions.

Bibliography

1. Madani A., *et al*. "Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease". *NPJ Digital Medicine* 1.1 (2018): 1-1.

2. Cano-Espinosa C., *et al*. "Automated Agatston score computation in non-ECG gated CT scans using deep learning". *In Medical Imaging: Image Processing* 2.10574 (2018): 105742K.

3. Bernard O., *et al*. "Deep learning techniques for automatic MRI cardiac multi-structures segmentation and diagnosis: is the problem solved?" *IEEE Transactions on Medical Imaging* 37.11 (2018): 2514-2525.

4. Singh Y., *et al*. "Geometrical evaluation of the Scar in Left ventricle using TDA". *In 2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC)* (2021): 0922-0925.

5. Acharya UR., *et al*. "Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals". *Applied Intelligence* 49.1 (2019): 16-27.

6. Zhang J., *et al*. "Fully automated echocardiogram interpretation in clinical practice: feasibility and diagnostic accuracy". *Circulation* 138.16 (2018): 1623-1635.

7. Thavendiranathan P., *et al*. "Feasibility, accuracy, and reproducibility of real-time full-volume 3D transthoracic echocardiography to measure LV volumes and systolic function: a fully automated endocardial contouring algorithm in sinus rhythm and atrial fibrillation". *JACC: Cardiovascular Imaging* 5.3 (2012): 239-251.

8. Otani K., *et al*. "Three-dimensional echocardiographic assessment of left heart chamber size and function with fully automated quantification software in patients with atrial fibrillation". *Journal of the American Society of Echocardiography* 29.10 (2016): 955-965.

9. Yashbir Singh., *et al*. "An Automated Method for Detecting the Scar Tissue in the Left Ventricular Endocardial Wall Using Deep Learning Approach". *Current Medical Imaging Reviews* (2019).

10. Deepa D., *et al*. "An automated method for detecting atrial fat using convolutional neural network". *Proceedings of the Institution of Mechanical Engineers Part H: Journal of Engineering in Medicine* 235.11 (2021): 1329-1334.

11. Alsharqi M., *et al*. "Artificial intelligence and echocardiography". *Echo Research and Practice* 5.4 (2018): R115-R125.

12. Brattain LJ., *et al*. "Machine learning for medical ultrasound: status, methods, and future opportunities". *Abdominal Radiology* 43.4 (2018): 786-799.

13. Singh Y., *et al*. "Cardiac Electrophysiology Studies Based on Image and Machine Learning (2018).

14. Singh Y., *et al*. "Effect of left ventricular longitudinal axis variation in pathological hearts using Deep learning". *Easy Chair* (2018).

15. Wang C., *et al*. "Lung nodule classification using deep feature fusion in chest radiography". *Computerized Medical Imaging and Graphics* 57 (2017): 10-18.

16. Brown LG. "A survey of image registration techniques". *ACM Computing Surveys* 24.4 (1992): 325-376.

17. Maintz JB and Viergever MA. "A survey of medical image registration". *Medical Image Analysis* 2.1 (1998): 1-36.

18. Audette MA., *et al*. "An algorithmic overview of surface registration techniques for medical imaging". *Medical Image Analysis* 4.3 (2000): 201-217.

19. Singh Y., *et al*. "Non-ischemic endocardial scar geometric remodeling toward topological machine learning". *Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine* 234.9 (2020): 1029-1035.

20. Lester H and Arridge SR. "A survey of hierarchical non-linear medical image registration". *Pattern Recognition* 32.1 (1999): 129-149.

21. Mäkelä T., *et al*. "A review of cardiac image registration methods". *IEEE Trans Med Imaging* 21.9 (2002): 1011-1021.

22. Bushberg JT. "The Essential Physics of Medical Imaging". Philadelphia, PA, USA: Lippincott Williams and Wilkins (2002).

23. Auricchio A., *et al*. "Accuracy and usefulness of fusion imaging between three-dimensional coronary sinus and coronary veins computed tomographic images with projection images obtained using fluoroscopy". *Europace* 11.11 (2009): 1483-1490.

24. Manzke R., *et al*. "Respiratory motion compensated overlay of surface models from cardiac MR on interventional X-ray fluoroscopy for guidance of cardiac resynchronization therapy procedures". In: Wong K. H., Miga M. I., editors. Medical Imaging 2010: Visualization, Image-Guided Procedures, and Modeling; March 2010; San Diego, CA, USA. International Society for Optical Engineering (SPIE) (2010).

25. Duckett SG., *et al*. "Advanced image fusion to overlay coronary sinus anatomy with real-time fluoroscopy to facilitate left ventricular lead implantation in CRT". *Pacing and Clinical Electrophysiology* 34.2 (2011): 226-234.

26. Ma YL., *et al*. "Clinical evaluation of respiratory motion compensation for anatomical roadmap guided cardiac electrophysiology procedures". *IEEE Transactions on Biomedical Engineering* 59.1 (2012): 122-131.

27. Panayiotou M., *et al*. "Image-based view-angle independent cardiorespiratory motion gating and coronary sinus catheter tracking for x-ray-guided cardiac electrophysiology procedures". *Physics in Medicine and Biology* 60.20 (2015): 8087-8108.

28. Wielandts JY., *et al*. "Multi-phase rotational angiography of the left ventricle to assist ablations: feasibility and accuracy of novel imaging". *European Heart Journal-Cardiovascular Imaging* 17.2 (2016): 162-168.

29. Marinelli M., *et al*. "Registration of myocardial PET and SPECT for viability assessment using mutual information". *Medical Physics* 37.6 (2010): 2414-2424.

30. Mahesh M and Cody DD. "Physics of cardiac imaging with multiple-row detector CT". *Radiographics* 27.5 (2007): 1495-1509.

31. Ropers D. "Detection of coronary artery stenoses with thin-slice multi-detector row spiral computed tomography and multiplanar reconstruction". *Circulation* 107.5 (2003): 664-666.

32. Yang GY., *et al*. "Automatic coronary calcium scoring using non-contrast and contrast CT images". *Medical Physics* 43.5 (2016): 2361-2373.

33. Bustamante M., *et al*. "Atlas-based analysis of 4D flow CMR: automated vessel segmentation and flow quantification". *Journal of Cardiovascular Magnetic Resonance* 17.1 (2015): 12.

34. Zhuang XH., *et al*. "A registration-based propagation framework for automatic whole heart segmentation of cardiac MRI". *IEEE Transactions on Medical Imaging* 29.9 (2010): 1612-1625.

35. Wang C., *et al*. "Fusion of color Doppler and magnetic resonance images of the heart". *Journal of Digital Imaging* 24.6 (2011): 1024-1030.

36. Pouch AM., *et al*. "Dynamic shape modeling of the mitral valve from real-time 3D ultrasound images using continuous medial representation". In: Bosch J. G., Doyley M. M., editors. Proceedings of Medical Imaging: Ultrasonic Imaging, Tomography, and Therapy; International Society for Optical Engineering (SPIE), San Diego, CA, USA (2012).

37. Leung KYE., *et al*. "Registration of 2D cardiac images to real-time 3D ultrasound volumes for 3D stress echocardiography". In: Reinhardt J. M., Pluim J. P. W., editors. Proceedings of Medical Imaging 2006: Image Processing; International Society for Optical Engineering (SPIE), Graz, Austria (2006).