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Radiomics in Echocardiography: Deep Learning and Echocardiographic Analysis

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Abstract

Purpose of Review Recent development in artificial intelligence (AI) for cardiovascular imaging analysis, involving deep learning, is the start of a new phase in the research field. We review the current state of AI in cardiovascular field and discuss about its potential to improve clinical workflows and accuracy of diagnosis.

Recent Findings In the AI cardiovascular imaging field, there are many applications involving efficient image reconstruction, patient triage, and support for clinical decisions. These tools have a role to support repetitive clinical tasks. Although they will be powerful in some situations, these applications may have new potential in the hands of echo cardiologists, assisting but not replacing the human observer.

Summary We believe AI has the potential to improve the quality of echocardiography. Someday AI may be incorporated into the daily clinical setting, being an instrumental tool for cardiologists dealing with cardiovascular diseases.

Keywords Artificial intelligence · Automated diagnosis · Deep learning · Echocardiography · Machine learning · Myocardial infarction

Introduction

Recent development in artificial intelligence (AI) for medical imaging analysis, involving deep learning, is the start of a new phase in the clinical setting. Existence, differential, and functional diagnosis with medical images is nowadays an active point of focus in the research field [1]. The latest field of AI using medical images for predicting clinical prognosis, disease stages, and pathology is called radiomics [2]. The suffix -omics is a term in molecular biology to describe the detailed characterization of biologic molecules. Recently, this word is used in other medical research fields (e.g., radiology) that generate much meaningful data from medical samples. The term "Radiomics" is mainly used for differential diagnosis in the medical imaging field. Thus, in cardiovascular medicine, analysis using echocardiographic images may be considered as a type of radiomics in a broad sense. The radiomics in echocardiography is gradually spreading to many research laboratories. Moreover, in the field of the echo radiomics, deep learning has been also applied as a new method for detection and classification of several diseases. Deep learning is able to extract detailed low-level information from the original image. It is also able to combine these to higher order structural information, allowing identification of complex entities from the images. This comprehensive review shows how radiomics in echocardiography involving deep learning has a potential to improve clinical workflows, and accuracy of diagnosis.

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Differences Between Machine Learning and Deep Learning

First, to understand the progress of radiomics in echocardiography involving deep learning, it is important to clarify the difference between machine learning and deep learning. Machine learning is a type of algorithm to analyze the data, learn from it, and then apply the same to make appropriate decisions [3]. The tasks in machine learning included Random Forest, Decision Tree, Support Vector Machines, naive

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Bayesian networks, and etc. In machine learning, the algorithm needs to be told how to make an accurate prediction by providing it with more information by analysts. The method should also be provided by the analysts. A computer with central processing unit is used to train the machine learning model during a short time.

Deep learning is a subset of machine learning that can solve a problem by using multilayered neural networks. The method is free from definitions by analysts, and the accuracy is relatively high for imaging. Datasets are needed in training a computer with graphics processing unit, requiring a longer time. A general issue to build a deep-learning model for a medical imaging task is access to a sufficiently large dataset [4]. However, the recent literature has many examples of non-deep learning projects that use thousands of datasets and deep learning projects that use hundreds [5, 6]. Both methods are technically compatible with arbitrary sizes of samples (Table 1). Deep learning for echocardiography might provide an insight to diagnostics with fewer errors and check hidden features for accurate diagnosis. Recently, developments in AI "deep learning" have become a point of focus in the echocardiographic field.

Process of Echocardiographic AI

Echocardiography is a useful method in the diagnosis and management of cardiovascular disease [7]. In the clinical setting, accurate and reproducible echocardiographic assessment is required [8–11]. Even with the progress of new methods (speckle-tracking, 3-dimensional echocardiography, and etc.), the final diagnosis is strongly dependent on observers' experience. Diagnostic error is a major unresolved problem [12–14]. Moreover, interpretations not only differ between different echo cardiologists, but the same physician may come to different conclusions while the same examination is repeated. A heavy workload in the clinical setting may lead to more errors, and methods with high reproducibility are needed. Echocardiographic AI may pose as a feasible solution to this problem.

The process of echocardiographic AI involves several steps of analysis (Fig. 1). The first step is the assessment of image quality. Acquiring of accurate images needs many years of experience. Poor quality images are sometimes acquired by less experienced observers and can negatively affect diagnostic accuracy. Thus, the assessment of image quality is very important [15]. A recent paper showed that the accuracy of AI-based classification for image quality was excellent (score error 0.11 ± 0.09). This proposed approach could also be generalized to other images involving deep learning in the cardiovascular field, where there are frequently gaps in clinical labeling [16].

Next step is the view classification and segmentation of cardiovascular structures. Echocardiographic images require many types of recordings due to the complexity of the heart structure. The view classification and segmentation of cardiovascular structures may be useful in automation of scans, or detection of appropriate views in the clinical setting. Several investigators showed a good accuracy for view classification (accuracy: around 91.7 to 94.4% for 15-view classification) [6, 17]. Recently, we reported on our newly developed view classification model based on CNN (convolutional neural network) using 17,000 images. In this model, there were 1.9% mislabeled images. Interestingly, the mislabeled cases seem to be difficult to determine even by expert observers. To determine if the 98.1% accuracy rate was acceptable for creating a feasible prediction model, we tested the prediction model for ejection fraction (EF) using learning data with a 1.9% error rate. The accuracy of the prediction model for EF was warranted, even with training data containing 1.9% mislabeled images. Thus, this approach may provide a clinically feasible method of view classification for analysis of echocardiographic data. [18]

In the next step, measurement and quantification of the morphological structures can be assessed for dimensions or volumes. Zhang et al. proposed a method based on a deep learning approach for a fully automated analysis of echocardiographic data [6]. Their model showed a mean absolute percentage error of approximately 10% for EF from the apical 2-chamber view, and 20% for EF from the apical 4-chamber view. Another paper showed that the EF based on AP2/AP4 views had a good correlation with reference EF (mean absolute deviation = 2.9%) [19]. Our recent report adds to this by demonstrating an even better performance of a deep learning algorithm when five views are utilized. In an independent cohort, a good correlation was found between estimated EF

Table 1 Differences between machine learning and deep learning for imaging

Factors	Machine learning	Deep learning
Dataset	Smaller dataset	Larger dataset
Accuracy	Lower accuracy	Higher accuracy depends on dataset
Training time	Shorter time	Longer time
Hardware	Central processing unit	Graphics processing unit
Definition	By the analysts	Self-directed

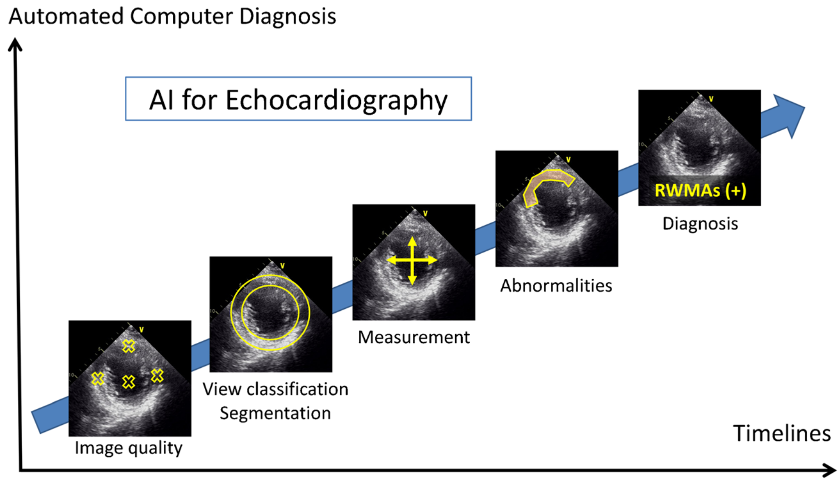

Fig. 1 Artificial intelligence (AI) involving deep learning and their tasks. RWMAs regional wall motion abnormalities

($r = 0.82$, $P < 0.001$). The area under the receiver-operating characteristic curve (AUC) for classification of reduced EF was 0.92 [20]. According to our results, it may be more accurate to make a prediction model for LVEF from multilevel images in the clinical setting. Based on these results, full automated EF measurements may be realized in the near future.

Last step is the field of computer-aided detection. This step may identify abnormalities in images for clinical assessment. The diagnosis is generated from the finding of abnormalities and is a computer-aided diagnosis. This concept is the high stage of automated computer diagnosis solely based on information from images. AI has the potential to improve analysis and interpretation of medical images to an advanced stage compared with previous algorithms. Table 2 summarizes the diagnostic ability of current deep learning models in the field of echocardiography [5, 6, 15–17, 19–24]. The remainder of this review is focused on previously published deep learning approaches for regional wall motion abnormalities (RWMAs).

AI for Assessment of Regional Wall Motion Abnormalities

One of the most important assessments in echocardiography is evaluating RWMAs for decision making in ischemic coronary artery disease (CAD). Assessment of RWMAs is a class I recommendation in the guidelines of multiple cardiovascular committees, created by experienced sonographers or echo cardiologists, for patients with chest pain the emergency department [25–27]. Conventional assessment of RWMAs is subjective and dependent on using visual judgment of endocardial movements and myocardial thickening [28]. An objective method to reduce the misreading of RWMAs is needed [29–31].

Strain imaging is widely used to check RWMAs. Strain imaging including speckle tracking methods (the pattern matching technique) is a noninvasive method of assessing LV global and regional function. Many studies published to use the strain imaging to assess myocardial function. For example, automated function imaging (AFI) has been developed to highlight potential RWMAs. The AFI algorithm noninvasively tracks and analyzes longitudinal strain based on speckle tracking and provides a single bull's-eye summary of the LV segmental wall strain values. AFI is expected to be tool to support clinical decision-making, by assessing LV function semi-automatically with a simplified operational procedure. Our previous study demonstrated that, the AFI algorithm was in agreement with the visual assessment of RWMAs by experts in myocardial infarction [30]. Sensitivity and specificity were greater with AFI than with the inexperienced observers' assessment. On the other hand, even if there are several strain imaging studies to assess the RWMAs, automated measurements of regional or wall-specific level are challenging because of significant variability and limited full automation.

Moreover, several institutes have various readers with a wide range of experience levels [32, 33]. For example, many interventions for reduction of variability in LV function have been tested to overcome this issue [12, 13]. Our multicenter group suggested that a simple teaching intervention can reduce the variability of LV assessment, especially in readers with limited experience [14]. However, there are several limitations including a lack of ground truth, limited number of sample sizes. Thus, diagnostic errors are a major unresolved problem.

Machine-learning models have been evaluated to identify and quantify RWMAs [23, 24]. Unfortunately, the accuracy of these models is limited. Recently, our group developed an AI model for automated detection of RWMAs in myocardial infarction, using a deep learning algorithm [5]. We retrospectively enrolled 400 patients with coronary angiography to evaluate coronary artery disease. We have selected good images with adequate acoustic detail on the basis of visualization of the LV walls and endocardium. Importantly, to overcome

Table 2 Studies of deep learning for echocardiography

	Year	Target	Training/ validation dataset	test dataset	Accuracy	AUC
Image quality						
Abdi et al. [15]	2017	Quality	6916 images	–	Score error 0.71 ± 0.58	–
Liao et al. [16]	2019	Quality	14,443 echo studies	–	Score error 0.11 ± 0.09	–
View classification						
Madani et al. [17]	2018	Echocardiography views	200,000 images	20.000 images	0.92	1.00
Zhang et al. [6]	2018	Echocardiography views	Total 14,035 studies	–	0.84	–
Kusunose et al. [18]	2020	Echocardiography views	17,000 images	189 subjects	0.98	–
Segmentation						
Zhang et al. [6]	2018	Chamber segmentation	Total 14,035 studies	–	64.6–89.8%	–
Leclerc et al. [21]	2019	Chamber segmentation	500 subjects	–	84%	–
Measurement						
Zhang et al. [6]	2018	LV size and function	Total 14,035 studies	–	Deviations 15 to 17%	–
Asch et al. [19]	2019	LV function	> 50,000 studies	99 subjects	$r = 0.95$	–
Kusunose et al. [20]	2020	LV function	17,000 images	189 subjects	$r = 0.92$	–
Leclerc et al. [21]	2019	LV function	500 subjects	–	$r = 0.82$	–
Ghorbani et al. [22]	2020	Size, function, clinical data	2850 subjects	373 subjects	–	0.75–0.89
Abnormalities						
Kusunose et al. [5]	2020	Wall motion abnormalities	1200 images	120 images	–	0.97
Raghavendra et al. [23]	2018	Wall motion abnormalities	279 images	–	0.75	–
Omar et al. [24]	2018	Wall motion abnormalities	4392 maps	61 subjects	0.95	–
Diagnosis						
Zhang et al. [6]	2018	Myocardial disease	Total 14,035 studies	–	–	0.85–0.93

the issue for the generalizability, we have gathered a separate validation group from an independent site. Detection of the presence of RWMAs and the territory of RWMAs was accomplished by a CNN. We used ResNet, DenseNet, Inception-ResNet, Inception, and Xception for a CNN [34–36].

We have compared the AUCs by several deep learning algorithms for detection of territories of wall motion abnormality. The largest AUC was ResNet (AUC 0.97), but there was no significant difference among algorithms except for the Xception model (ResNet: AUC 0.97; DenseNet: AUC 0.95; Inception-ResNet: AUC 0.89; Inception: AUC 0.90; and Xception: AUC 0.85, vs. other algorithms, $p < 0.05$). For detection of the presence of RWMAs, the AUC by deep learning algorithm was similar to that of an experienced cardiologist/sonographer (0.97 vs. 0.95, $p = 0.61$), and significantly higher than the AUC by resident physicians (0.97 vs. 0.83, $p = 0.003$). Interestingly, deep learning had relatively low ratios of misclassification for the right coronary artery, left circumflex coronary artery, and control groups, except for the left anterior descending coronary artery (LAD). It seems to reflect the real-world assessment (e.g., overdiagnoses in ischemic groups by human observers or importance of LAD in the clinical setting). The results of such a deep learning model in echocardiography might provide new insights in the medical field.

Finally, we should consider the limitation of deep learning. The reason of different algorithms may behave differently is unclear. In our study, we apply five models to differentiate echocardiographic images. Basically, the number of parameters and layers are difference among the models employed in this study. One of the advantages in use of a deep learning model over the other types of machine learning model is the construction of the appropriate features automatically developed in the intermediate layers. On the other hand, this may also make a reason why a specific model is superior to the other one unclear. Unfortunately, there is no clear explanation in this field and this problem is the "black box" issue.

Conclusions

Although there are several concerns about the required large dataset and "black box" algorithm, AI can provide appropriate results in the clinical setting. Cardiologists will require to be acquainted with new knowledge in the era of AI. In the medical AI imaging field, there are many applications involving efficient image reconstruction, patient triage, and support for clinical decisions. These tools have a role to support repetitive clinical tasks. Although they will be powerful methods in clinical situations, these applications may possess new potential in hands of echo cardiologists, assisting but not replacing the human observer. We believe AI has the potential to improve all fields of cardiovascular imaging, including echocardiography. In the near future, radiomics in echocardiography may be incorporated into the daily clinical setting, becoming an instrumental tool for cardiologists dealing with cardiovascular diseases.

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Compliance with Ethical Standards

Conflict of Interest The author has no conflicts of interest to declare.

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