Deep Echocardiography: A First Step toward Automatic Cardiac Disease Diagnosis Using Machine Learning

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Abstract

Echocardiography, the use of ultrasound waves to investigate the action of the heart, is the primary physiological test for cardiovascular disease diagnoses. Firstly, this article discusses the common diagnostic procedures of echocardiography, meanwhile emphasizes and elaborates that view recognition is the first essential step, and then explicates issues concerning manual view identification based on two main aspects i.e. echo images' properties and sonographers' task difficulties. Secondly, the published articles within the past five years relating to how artificial intelligence is applied to the echocardiographic view recognition are selected, compared and summarized. It is found that compared with previous machine learning algorithm, deep learning has the ability to boost the analysis and interpretation of ultrasonic images into a new level. Finally, the challenges and limitations existed during the development of AI in health care are highlighted and discussed.

Keywords: Artificial intelligence, View recognition, Deep learning, Echocardiography, Machine learning

1 Introduction

Cardiovascular diseases (CVD), including heart diseases and stroke, account for one-third of deaths worldwide and are considered as a global issue [1]. An echocardiogram, which is an ultrasound scan of the heart, plays an essential part of cardiovascular disease treatment and control, due to the high portability and low cost of the ultrasound devices. During the routine clinical examinations of heart disease, two-dimensional real-time echocardiography is often used. For instance, a cardiologist usually detects the left ventricle boundaries of both end-systolic and end-diastolic, and then uses it to provide a quantitative analysis of cardiac function for diagnosing certain heart diseases [2]. For some superpowers in the world, e.g. USA and China, a full echocardiographic diagnosis involves four main procedures. First of all, a cardiac sonographer scans the heart of a patient via the ultrasonic imaging device. By moving and positioning the transducer, the sonographer generates two or three seconds of short videos clips of the heart from different perspective [3]. Different views show different structures of the heart. Secondly specific anatomical structures can be manually delineated and measured [4]. For example, the diameter of anteroposterior left atrial (LA) is measured perpendicular to the aortic root long axis at end ventricular systole from the parasternal long axis view, which provides the explanation of left atrial appearance and also the references to certain heart diseases [5]. Thirdly, after the required echocardiographic measurements are performed and obtained in each single view, the cardiac sonographer will compose an official standardized report for this echocardiographic study, which should comprise the following sections: (1) Demographic and other identifying information, (2) echocardiographic evaluation, such as cardiac structures and quantitative measurements, and (3) descriptive summary [6]. Finally, the cardiologist will refer to the statistics and information reported to make a clinical diagnosis and give recommended treatments. Note that echocardiography is not the only method to perform cardiac investigations. A common sequence for echocardiographic diagnosis is illustrated in Figure 1.

Hence, in echocardiography accurate view identification is the first step in the follow-up measurement, analysis and diagnosis of echocardiography. One of the main objectives in this paper is to show causes leading to low accuracy, which is regarded as the most common problem from manual cardiac view interpretation are explicated meticulously based on two main aspects of echo images' properties and sonographers' career struggles. This article will also introduce the current research and application status of artificial intelligence

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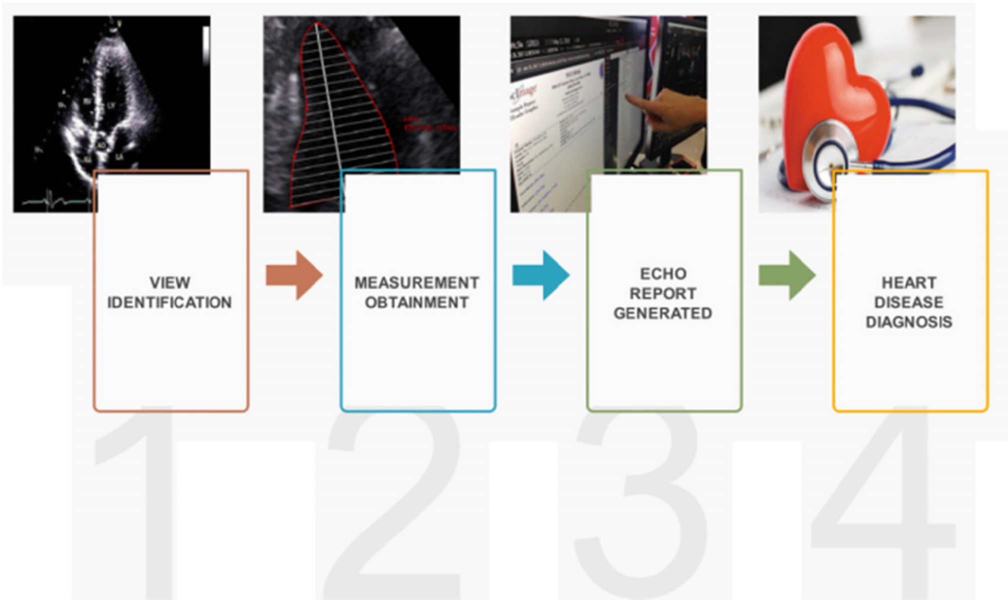

Figure 1. The echocardiographic diagnosis procedures

in the view recognition, and concludes that machine learning is the major adopted method, especially deep learning.

Finally, this paper points out the challenges and limitations during the development of AI in health care.

2 Low Accuracy Exists as the Most Common Problem for the View Recognition by Operator-Dependent Manual Work

In 1980, the American Society of Echocardiography Committee recommended six locations (Acoustic windows) that allow the ultrasound signal to reach the surface of the heart, including left and right parasternal, left and right apical, suprasternal and subcostal. The committee also recommended three standard imaging planes which are perpendicular to each other to observe the heart structure as shown in Figure 2 (1. Long-axis plane: parallel to the central axis of the left ventricle; 2. Short-axis plane: perpendicular to the long-axis plane; 3. Frontal plane: show four-chamber view of the heart), it meanwhile illustrated the operating specifications of how to obtain this series of standard views [7].

However, low accuracy for view recognition and diagnostic errors are still major unsolved problems. If the disease is misdiagnosed, it can progress to more fatal heart failure. One research has shown that echocardiographic assessment inaccuracy levels can unexpectedly be as high as 30 percent of echo tests and echocardiographic quality in 24 percent of imaging studies is inadequate [8]. Since each echo study is interpreted manually by the specialist, it can be confirmed that the operator's technical skills and experience levels will make huge influences on the final analysis. The European Association of Echocardiography has suggested a total of 350 exams to gain specific competences for regular TTE [9]. Interpretation of medical imaging therefore requires extensive and time-consuming preparation, which is particularly difficult for new learners. Moreover, not only do cardiologists vary in the interpretation of images, but the same observer may come to different conclusions when measurements are repeated because the physician has changed his or her views or status at a certain time [10]. On the other hand, one survey has reported that the sonographers and even half of cardiologists are more prone to experiencing overwork [11]. Loss of work interest and negative attitude could lead to diagnostic errors since the high degree of concentration is needed during the operation process. In addition, the limited time for clinical visits is considered to be another important reason for interpreting errors, due to the growing burden of cardiovascular disease worldwide. More and more of these professionals now face an unprecedented time crunch as they rush through their appointments to perform and interpret an increasing amount of procedures [12].

Apart from sonographers' interpretations themselves, when comparing natural images, the characteristic properties and quality of echocardiographic clips and images are the second main aspects for interpreting inaccuracy. Among them are:

(1) The intra-view variability: for two factors the presence of images caught in the same heart view can vary for different patients. (i) The patients' heart anatomy differs significantly, depending on their physical features. (ii) There is no clear marker zone for positioning the transducer on the body of patients [13].

(2) The inter-view similarity: while in appearance, as presented in Figure 2, several images might appear similar, e.g. Parasternal Short Axis of Mitral Valve and Parasternal Short Axis of Apex levels, especially when viewed in video form, showing the moving heart

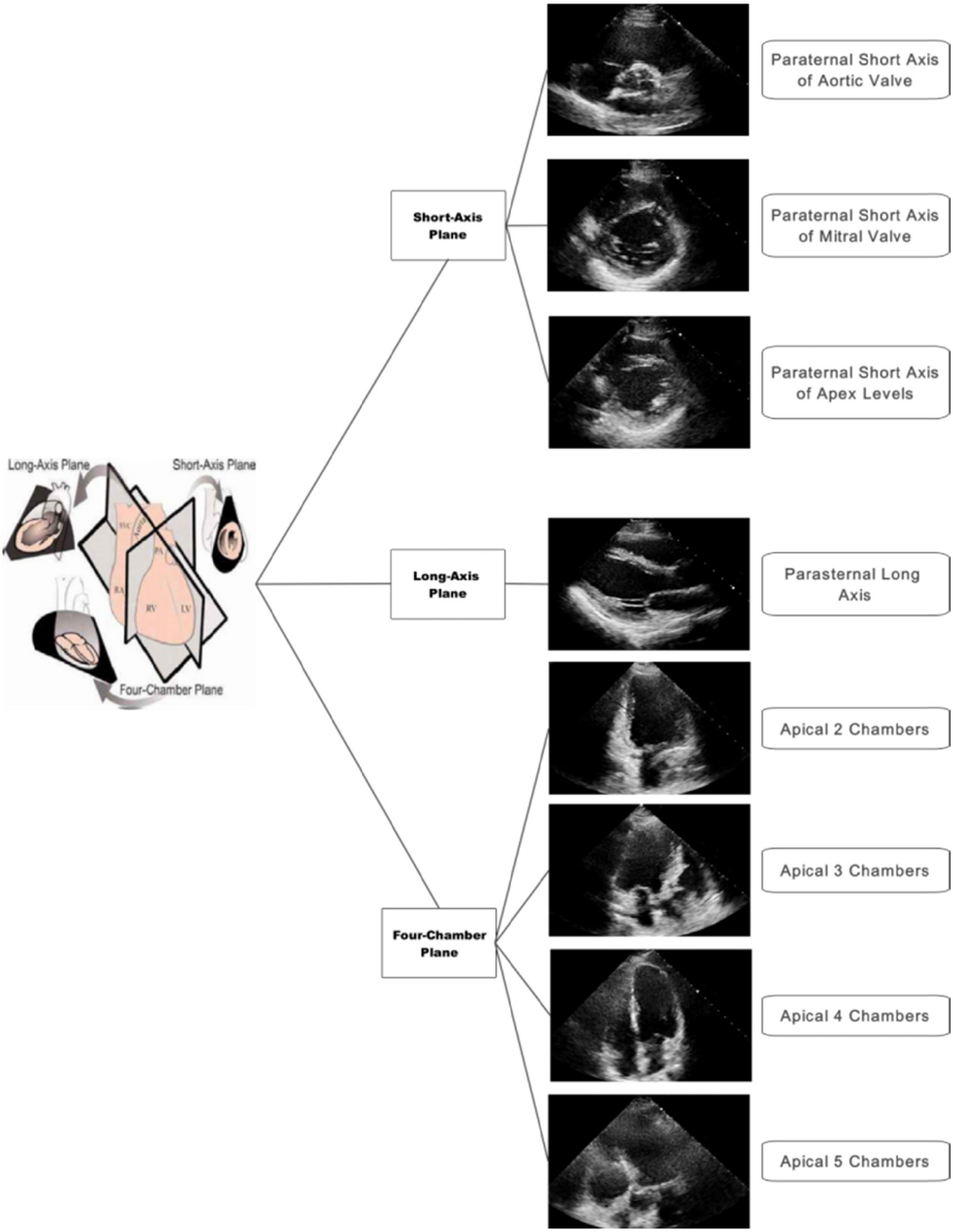

Figure 2. Diagram of the three orthogonal imaging planes used to visualize the heart with two-dimensional echocardiography and the illustration of eight views of echocardiograms

bordering on two separate points of view [3].

(3) Too much speckle noise and clutter noise: medical ultrasound images have poor quality at times due to lots of speckle noise and clutter noise, which will result in difficulty distinguishing and judging the details in images [14].

(4) Extra artifacts and signals: due to the anisotropy of acquiring ultrasound images, artifacts formed by lobular calcification and a huge attenuation of signals may reduce the quality of images [15].

Figure 3 shows and summarizes the causes for low accuracy of interpreting echocardiograms based on two major aspects of echo images and sonographers.

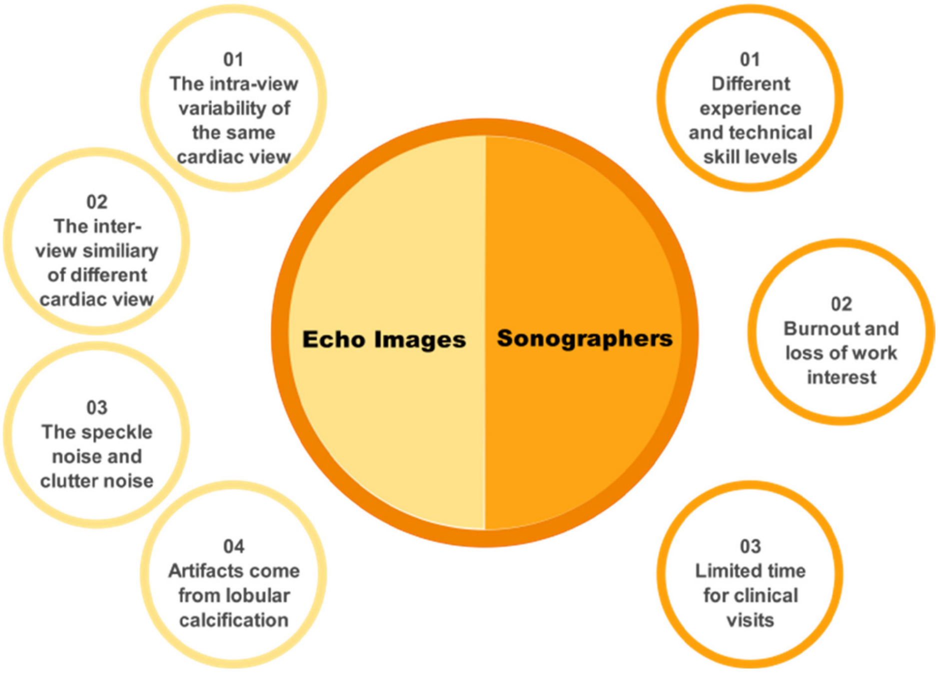

Figure 3. Finding valid cardiac views has been difficult and diagnostic errors are a major unresolved problem. This diagram shows the causes for low accuracy of interpreting echocardiograms based on two major aspects of echo images and sonographers

3 Artificial Intelligence for View Identification of Echocardiogram

The recent interest in using artificial intelligence techniques [16-17] may offer a solution to increase the interpreting accuracy and reduce physician workload, in addition to removing repetitive and tedious tasks. Especially for the automatic recognition of echocardiographic view, a first step towards echocardiographic image analysis, current researchers focus on the machine learning approaches and image processing methods as shown in Figure 4. Several studies have now demonstrated that using general machine learning methods can accurately and efficiently classify different echocardiographic views. As early as 2004, Shahram et al. proposed the use of Markov random chain for the first time to design a universal chamber template to detect cardiac chambers to assist in the identification of three types of standard cut planes. However, additional signals are required to specify the end-diastolic (ED) section [38]. Based on the multi-category lifting algorithm framework, Kevin et al. extract Haar rectangular features to train a classifier, but also need to detect the spatial position of the heart chamber to assist in the identification of four types of standard cuts [39]. On the basis of statistical analysis of the spatiotemporal details of the beating heart, Beymer et al. used active appearance models to model shapes and textures, statistically tracked a cardiac cycle and projected it into the motion space for classification [40]. Review the past ten years, Table 1 selects three published journals which focus on traditional machine learning methods [18] regarding to distinguishing echocardiographic view automatically. Balaji found that back propagation neural network with histogram features provides a satisfactory 87.5 percent efficiency to differentiate four standard views [13]. During the same year, Li proposed a different approach by extracting feature points using KAZE and coupling with BoW representation method, which gives the accuracy of 81.09 percent for eight viewpoints [19]. However, when only three main views are distinguished, 97.44 percent accuracy can be achieved, assuming that the more view locations, the more difficult the task is. Since the echocardiography is an ultrasound scan of the moving heart, Khamis used spatio-temporal extraction features (cuboid detector) and supervised dictionary learning approaches to classify different apical views with approximately 95 percent accuracy [20]. These traditional machine learning methods can be summarized into two stages: initially the image can be represented by prior manual design features [21-22], and then different ML classification methods [23-24] are applied to model and analyze these feature vectors. However, the models based on specific manual design features usually lead to poor generalization performance due to the problem of semantic gap.

In recent years, the deep convolutional neural network [25-26] has shown far better performance than traditional methods on large-scale natural images dataset, e.g. ImageNet [27]. It is attributed to deep learning that uses a large amount of labeled data to start from the original pixels of the image, and hierarchically learn the high-level abstract semantic features of the image layer by layer [28].

Table 1. The published journals within the past five years focus on traditional Machine Learning approaches regarding to distinguish echocardiographic view automatically

No	Reference	Research Objectives	Theory/Methods	Findings/Conclusions	Limitations
1	Automatic classification of cardiac views in echocardiogram using histogram and statistical features [13]	Based on machine learning methods, suggesting a thoroughly computerized classification of cardiac view in echocardiogram.	✓ Two features: histogram and statistical features ✓ Two classifiers: BPNN and SVM	✓ The BPNN with histogram features provides 87.5 percent better performance.	The percentage is not accurate enough.
2	The Application of KAZE features to the classification echocardiogram videos [19]	To offer a different approach using the emerging KAZE method by extracting feature points.	✓ Feature extraction: KAZE ✓ Feature representation: BoW, sparse coding, FV ✓ Classification approach: SVM ✓ There is also contrast with SIFT methods.	✓ KAZE method seems to outperform SIFT when it is utilized to the challenge of classification on a series of echocardiograms.	Most of the mistakes arise within the A5C and PSAM classes because of the limited size of the training data in these two groups.
3	Automatic apical view classification of echocardiograms using a discriminative learning dictionary [20]	Proposing a fully automated classification algorithm for apical echocardiogram views.	✓ Extract spatial & temporal information using cuboid detector(s) ✓ Classification based on supervised dictionary learning	✓ Accuracy is higher than without the cuboid detector. ✓ The 2100 dictionary size yielded maximum precision.	1. Derived from LC-KSVD scheme. 2. Due to the linear classification used, it could not precisely distinguish none linearly separable cases.

Table 2 compares five published journals based on deep learning methods within the past five years regarding to distinguishing echocardiographic view automatically. Zhang used a deep architecture with 13 layers, considered a large number of echocardiography view classes (23 views), applied to a large data set (14035 echocardiograms), and reported an 84 percent accuracy overall (including partially obscured views) [31]. However, at present the theoretical analysis of deep convolutional neural network is not complete, and the working mechanism of automatic learning of semantic features is still a "black box". Therefore, the accuracy rate seems the fairest evaluation standard for comparison of different models, and how to obtain the excellent generalization ability comes from is still an open question. Madani attempted occlusion testing and saliency mapping to assist in getting inside the black box, and concluded that overall test accuracy decreased dramatically when clinically important cardiac features were masked [29]. As redundant information independent of the view, such as exam information (time and date of test, heart rate, ECG) and scanner details, appears on any echocardiogram and can corrupt the classification process, Madani and colleagues further demonstrated a group of CNNs with a single U-net to segment the field of view and showed 94.4 percent precision [30].

Temporary information on how features, such as heart valves or ventricular walls, shift during the cardiac cycle is often overlooked and skipped, some studies have extended the state of the art of deep learning convolutional neural network to the classification of echocardiographic video images. Table 3 summarizes two published journals using fused network to distinguish echocardiographic view automatically. Gao has developed a two-strand CNN architecture, integrating both spatial and temporal information sustained by the moving heart's video images [3]. Howard compared four types of neural network architectures and concluded at last that the most effective network is a "Two Path" network with input for both spatial and optical flow, with just 3.9 percent of the corresponding error rate [33]. These improvements in greater precision can be related to the ability of this network to monitor the movement of certain structures. We believe that deep learning techniques such as RNN and LSTM which use temporal information can further improve the

Table 2. The published journals within the past five years focus on Deep Learning methods regarding to distinguish echocardiographic view automatically

No	Reference	Research Objectives	Theory/Methods	Findings/Conclusions	Limitations
1	Fast and accurate view classification of echocardiograms using deep learning [29]	To check whether supervised deep learning with CNNs can be used to identify views automatically without requiring prior manual selection of feature.	✓ CNN including six convolutional layers and two fully-connected layers ✓ A simple majority vote in classification is applied to video clips	✓ Deep learning completes the classification of expert views.	Accuracy was poor for clinically similar views and with fewer training data.
			✓ Perform occlusion testing and saliency mapping to get inside the black box of CNN	✓ Model classification is based on regions of cardiac images.	
2	Deep echocardiography: data-efficient supervised and semi-supervised deep learning towards automated diagnosis of cardiac disease [30]	Using pipeline supervised models and developing semi-supervised generative adversarial network models for prediction tasks in cardiology.	✓ Adopting VGG16-like architecture	✓ Find optimal balance between classifier performance and computational burden at 120*160 pixels.	1. Classification of images is just one aspect of clinical diagnosis. 2. Our sample sizes are limited.
			✓ U-net for FoV segmentation	✓ With the FoV, the accuracy of 94.4% is reported.	
			✓ Semi-supervised GAN model is applied when labeled data is limited	✓ When labeling data is minimal, GANs can achieve better results than traditional CNNs.	
			✓ Transfer learning	✓ LV segmentation and transfer learning allow LVH to be categorized effectively.	
3	Fully Automated Echocardiogram Interpretation in Clinical Practice [31]	Using a combination of computer vision methods to provide a fully integrated computer vision pipeline for analysis of cardiac structure, function and disease detection.	✓ 13-layer convolutional neural network for view classification ✓ Clustering the top layer output by t-Distributed Stochastic Neighbor Embedding	✓ The model accurately identified views, including highlighting partially obscured cardiac chambers, and permitted individual cardiac chambers to be segmented.	Avoid the loss of information from low-cost devices.
4	Automated Interpretation of Echocardiograms Technical Milestone Report [32]	Aim to speed up the view identification, CNN is used, with weights transferred from another trained model, to classify the image data into eight standard echo views.	✓ An echo view classification CNN was built with 500-500-8 last three fully connected layers ✓ Transfer learning is applied	✓ The model reached the highest validation accuracy (93.94 percent) on the 5^{th} epoch.	Improvements can be seen on the correct classification of PSAX-MV and A2C views.

Table 2. The published journals within the past five years focus on Deep Learning methods regarding to distinguish echocardiographic view automatically (continue)

No	Reference	Research Objectives	Theory/Methods	Findings/Conclusions	Limitations
5	Real-Time Standard View Classification in Transthoracic Echocardiography Using Convolutional Neural Networks [34]	1. Develop fully automated, stable, real-time CVC methods. 2. Examine the feasibility of using these methods to automatically extraction of 2-D views from 3-D volumes and orientation guidance for finding optimal views in 2-D US.	✓ Inception architecture was employed ✓ Our proposed network is a combination of introduced concepts ✓ Using majority	✓ The network proposed had a handful of trainable parameters and acquired inferences in real time with excessive precision.	To support this statement, it is necessary to introduce separate clinical studies on training effects, standardization, and workflow.
			✓ Comparison between models trained with 2D data and 3D data	✓ Using sliced of 3-D volumes for training greatly improved the performance.	

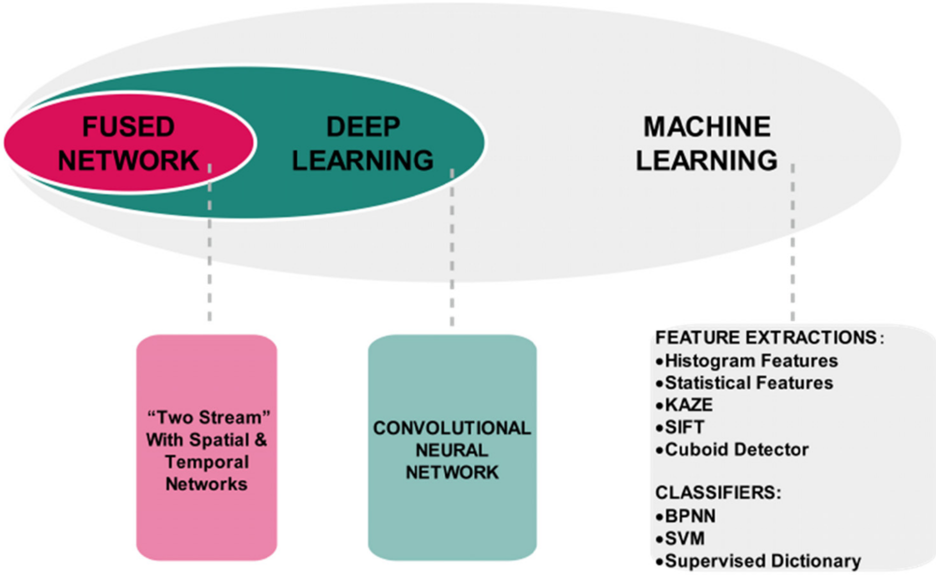

Figure 4. The methods applied to automatic cardiac view recognition

Table 3. The published journals within the past five years focus on fused network regarding to distinguish echocardiographic view automatically

No	Reference	Research Objectives	Theory/Methods	Findings/Conclusions	Limitations
1	A fused deep learning architecture for viewpoint classification of echocardiography [3]	For the classification of echocardiographic videos of eight perspective groups, a fused CNN structure is proposed.	✓ Integrating spatial as well as time information ✓ Dense optical flow is used to provide knowledge for temporal motion	✓ The CNN architecture of "Two Path" networks performs the best with 92.1 percent accuracy.	The total number of data is not significantly large.
			✓ Comparison with handcrafted approaches also takes place	✓ When the data sets are small in number, the hand-crafted methods can accomplish just as much.	

Table 3. The published journals within the past five years focus on fused network regarding to distinguish echocardiographic view automatically (continue)

No	Reference	Research Objectives	Theory/Methods	Findings/Conclusions	Limitations
2	Improving ultrasound video classification: an evaluation of novel deep learning methods in echocardiography [33]	Explore the efficacy of modern CNN architectures, including time- and two-stream networks.	✓ Comparison amongst single body classification with 2D CNN, multi-body classification with TD CNN, spatio-temporal convolution with 3D CNN, "Two Path" classification with spatial & temporal networks	✓ The best-performing classical 2D CNN design was Xception. ✓ The "Two Path" networks showed the very best accuracy, with the network based on the time-distributed CNN. ✓ The types of misclassification are very similar to human experts.	The extra several the view categories, the extra tough the project of the neural network.

performance of cardiac disease diagnosis.

Table 4 summarizes and compares the output categories, input data size and overall accuracies for current cardiac view identification approaches being proposed. The Østvik team offers the highest degree of precision so far, which is 98.9 percent, based on eight standard views [34]. Moreover, in Figure 5 the vertical values represent the overall recognition levels and the horizontal values indicate the scale of dataset for different model. It is worth mentioning that it doesn't reflect clear correlation since the number of output categories is different. All the preceding studies have demonstrated strongly the capacity of qualified AI-based models to recognize typical echocardiographic views. It should also be emphasized here that since the prediction accuracy of the deep learning model is influenced by the size of the traning set and the number of categories, generally speaking, the smalller the dataset, the more the calssifcation targets, the more difficult the model traning would be, resulting in poor prediciton performance. Therefore, evaluationg the consistency of the model based only on the final precision is unrigorous and unreasonable.

As mentioned above, determination of the view is the imperative first step in decoding an echocardiogram. Nevertheless, deep learning has shown great application prospects in the other essential parts of echocardiography, and it is expected to revolutionize the traditional computer-aided diagnosis (CAD) system that plays a significant role in precise image diagnosis.

The current Cardiac CAD research mainly focuses on four parts, as shown in Figure 6. Cardiac quantification and function is one the emphases of growth [35]. For instance, by accurately segmenting the left area of the heart (including the left ventricle and the left atrium), physicians can further assess the volume of the ventricle and the atrium. Meanwhile, necessary physiological parameters such as ejection fraction (EF) can be obtained [36]. Successful CAD software can improve the accuracy and timeliness of the image diagnosis, reduce the workload of doctors, and avoid misdiagnosis of late clinical treatments.

4 Limitation, Challenges and Future

Despite artificial intelligence bringing many benefits and progress in the diagnosis and treatment of cardiac disease, there are still challenges and limitations to overcome.

Table 4. The comparison table of output categories, input data size and overall recognition accuracies among existing models

References	Categories (No of Views)	Data Size (No of Videos)	Overall Accuracy (%)
Balaji et al.	4	200	87.5
Li et al.	8	312	81.1
Khamis et al.	3	309	95
Madani, Arnaout, et al.	12	3204	97.8
Madani, Ong, et al.	15	4005	94.4
Zhang et al.	23	14035	84
See et al.	8	3904	93.94
ϕstvik et al.	8	7000	98.9
Gao et al.	8	432	92.1
Howard et al.	14	9098	96.1

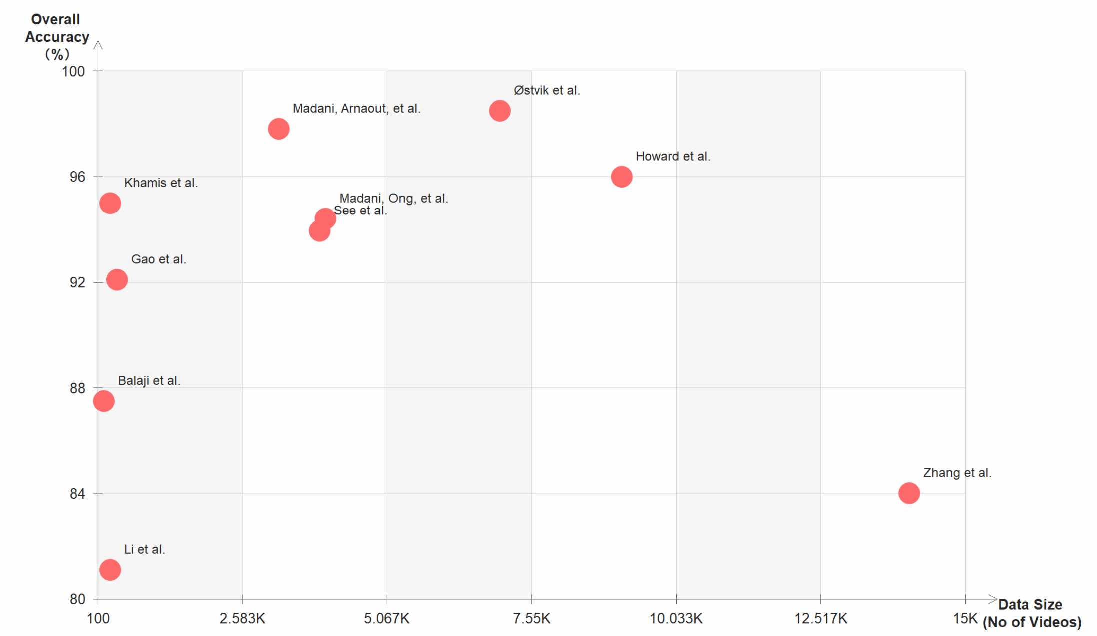

Figure 5. The scatter plot visualizes the relationship between experimental results and scale of dataset of different existing proposed approaches for cardiac view identification

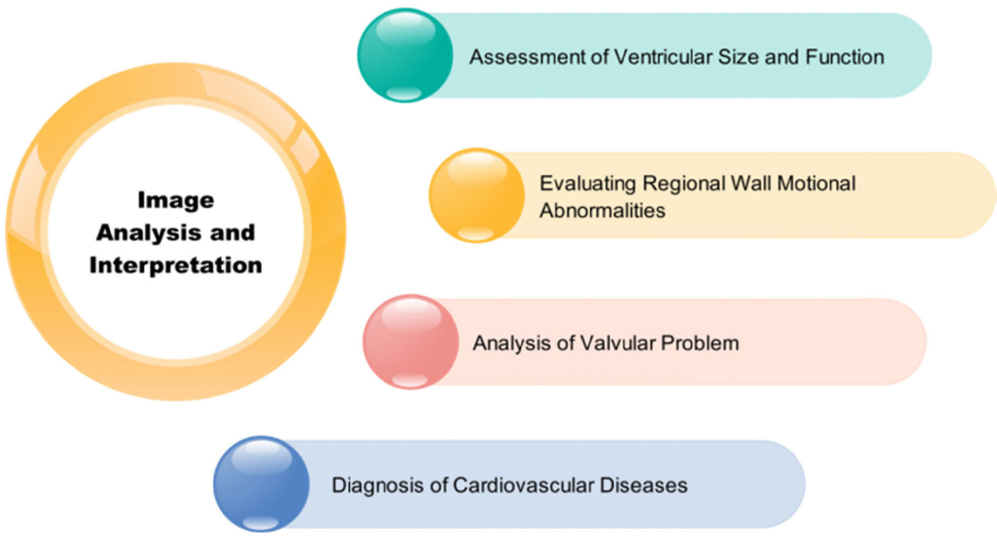

Figure 6. The current Cardiac CAD research focuses on four parts

The first problem is the clinical data acquisition and privacy protection. At this stage, the accuracy of artificial intelligence model depends on the size of the data-set, that is, the more data collected the more accurate the result will be. But the clinical data involves various aspects of patients' private information, so the regulatory requirements are very high. In addition, medical picture labeling is complex and takes medical professionals time, making it substantially more costly compared to other computer vision tasks [30]. Even if the problem of data collection and labeling is solved, the safety and integrity of the data has become a new issue faced by regulation of medicial devices. Wireless intrusion detection and wireless terminal access authentication can both be used to ensure wireless network security. Wireless intrusion detection technology means that the wireless network system will report to the wireless controller and refuses illegal wireless devices access to the hospital wireless network. At the same time, certain software- and hardware security measures can also play a very effective protective effect, such as wireless network reprogramming, network communication architecture design, secure routing protocol, emergency response scheduling mechanism, etc.

Secondly, different models were carried out and tested on their own private data set. However, there was evidence of variations in the physiological and anatomical structures of the heart that could be related to racial and ethnic variations, and the standard reference values of echocardiographic measurements were provided by different countries to their own citizens [37]. Therefore, the lack of generalization is still a big issue. Even if one model had shown a high accuracy rate on one specific data set, but it may not be feasible on another data set.

The third challenge is the legal matter in the artificial intelligence utilization. The error rate of AI is comparatively low, but it does not guarantee that no misjudgment will occur. Whether doctors, vendors, and medical institutions should bear the responsibility for risks individually or they should be jointly taken seriously during the development process. The clarification and division of medical responsibilities also contribute to the implementation of telemedicine projects. Mobile healthcare has changed the traditional way of life where people used to go to the hospital to seek for medical advices. Now whether at home or on the road, people are able to get a variety of health-related information from specialists.

With the continuous enhancement and the informationzation and intelligence standard of hospital management, the convergence of AI and medicial industry has become the inevitable path of future medical development. At present, artificial intelligence technology shows its predictable prospects in the field of heart disease diagnosis. Automated cardiac motion quantification (aCMQ) provides a method for evaluating the overall and segmental cardiac function. It is based on two-dimensional speckle tracking technology and provides a set of measurement tools and series of quantitative parameters without angle dependence, so the evaluation of myocardial movement measurement results are more accurate [24]. Intelligent three-dimensional ultrasound imaging is simple and easy to perform, and is able to automatically recognize the fetal heart standard views. It can also obtain the best image with one click and complete the automatic detection of related parameters without manual adjustment [41]. More research also suggests that the future joint development of robotic arms and image automation analysis is expected to achieve the acquisition, recognition and quantitative analysis of fully automated echocardiography without human intervention. It is actually already available to carry out real-time echocardiography analysis on a portable computer. According to the following, the embedding of deep learning related algorithm models is expected to bring broader development prospects for AI in the diagnosis of heart diseases compared with other traditional machine learning methods in the current research.

5 Conclusions

In the contemporary era of rapid development in information technology, how to properly integrate artificial intelligence technology with medicine in order to assist medical staffs in the diagnosis and treatment of disease has been a subject undergoing intense study. Echocardiograms are complicated and physicians need to spend numerous amounts of time to learn the interpretation of the standard cardiac views, moreover, low accuracy is regarded as the most common problem for the view recognition by operator-dependent manual work. From the reviews of past published journals, machine learning algorithms are able to recognize echocardiographic views automatically with surprisingly high accuracy. In particular, compared with previous machine learning algorithm, deep learning has the ability to boost the analysis and interpretation of ultrasonic images into a new level. Although there are still challenges concerning these studies, it is believed that artificial intelligence will have more progress and potential in the fields of echocardiography.

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