International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161

Available at http://inpressco.com/category/ijcet

Research Article

Automatic Quality Assessment of Echocardiograms on apical four-chember using Deep Convolutional Neural Networks

Miss. Priya R. Shinde and Dr. (Mrs.) S. K. Wagh

Department of Computer Engineering, MESCoE, Pune, India

Received 10 Nov 2020, Accepted 10 Dec 2020, Available online 01 Feb 2021, **Special Issue-8 (Feb 2021)**

Abstract

The neural network has been used in health care with many features. The basic concept of neural network is interconnection between neurons or input layer and hidden layer. The neurons considering the weight while interacting with each other. This paper proposes convolutional neural network in medical diagnosis. It uses the term echocardiography. The echocardiography is nothing but the internal structure of a patient's heart is studied through images. Echo is used to find the abnormalities in the images which are created by the ultrasound waves. The motivation behind this system is to decrease the overhead of the cardiologist. Result of this work is to figure out the abnormality in the patient's heart. Since, the cardiologist may take more time to pointing out the defect or may miss the defect in the heart. In this approach there are fourchamber view. The four- chamber view consider four chambers of heart like, right atrium, right ventricle, left atrium, left ventricle. This is a powerful approach which can detect the defect in the heart which human eye may be ignore.

***Keywords**: Convolutional neural network; deep learning; quality assessment; echocardiography; apical four chambers.*

Introduction

Health analytics is used extensively in health care for various purposes including reducing length of stay, and improving patient satisfaction with care. Health care analytics improves overall quality of patient care by exploring clinical outcomes and risk tolerances. Neural network, as health care analytic technologies have been successfully deployed in health care domain. Because of their ability to perform input output mapping of data without a priori knowledge of distribution patterns of data, these are appropriate for applications that deal with large volumes of data and with noisy data. Deep learning approximates the capacity of the human brain to alter synaptic connections between neurons as new information is introduced. In modeling disease likelihood in patients, statisticians may utilize logistic regression to estimate the appropriate weights for each input variable, which correspond to disease characteristics. Neural networks are useful when the interactions between disease characteristics are complex and manifold. To accommodate the interaction between disease features, neural networks often employ a layer of "hidden features", and each layer depends on the features of the preceding layer. In previous work [11], Amir H. Abdi investigated the feasibility of using convolutional neural networks to assess the quality of echo data. Here, we expand on that work and propose a framework for optimizing the deep learning architecture to generate an automatic echo score (AES) in real time. Our framework incorporates a regression model, based on hierarchical features extracted automatically from echo images, which relates images to a quality score determined by an expert cardiologist.

Literature Survey

Amir H. Abdi, Christina Luong, have proposed system is to reduce user variability in data acquisition by automatically computing a score of echo quality for operator feedback. To do this, a deep convolutional neural networks. For scoring apical four-chamber (A4C) echo. In this research, 6,916 end-systolic echo images were manually studied by an expert cardiologist and were assigned a score between 0 (not acceptable) and 5 (excellent). The images were divided into two independent training-validation and test sets. The network architecture and its parameters were based on the stochastic approach of the Particle Swarm Optimization on the training-validation data. The mean absolute error between the scores for the ultimately trained model and the expert's manual scores was 0:71±0:58. The reported error was comparable to the measured intra-rater reliability. The learned features of the network were visually interpretable and could be mapped to the anatomy of the heart in the A4C echo, giving confidence in the training result. The computation time for this network architecture, running on a GPU, was less than 10 ms per frame, sufficient for real-time deployment. This approach has the potential to facilitate widespread use of echo at the point-of-care and enable early and timely diagnosis and treatment. This approach did not use any specific assumptions about the A4C echo, so it could be generalizable to other standard echo views. It has been suggested that providing real-time quality feedback during image acquisition encourages less experienced sonographers to acquire echo images of better quality. In an attempt to provide such feedback, they propose a framework for automatic quality assessment of echo data. This procedure is costly for the healthcare system. Therefore, their ultimate goal is to improve echo by reducing observer variability in data acquisition using a realtime feedback mechanism that helps the operator to readjust the probe and acquire an optimal echo [11]. Lasse Lvstakken and Fredrik Orderud have proposed, a method for the visualization of the effective aperture of phased-array transducers is described. The method operates in real-time during acquisition, and can indicate if a contiguous part of an aperture does not contribute in the image formation. They believe the method can be help ensure that a good image quality is obtained in contexts where the acoustic contact or window is likely to be reduced. The method is based on the k-space formulation of the ultrasound imaging system, which has proven useful for investigating imaging system performance [1]. Pierrick Coup, Pierre Hellier, Charles Kervrann, and Christian Barillot have an adaptation of the nonlocal (NL)-means for speckle reduction in ultrasound (US) images. Originally developed for additive white Gaussian noise, they propose to use a Bayesian framework to derive a NL-means filter adapted to a relevant ultrasound noise model. Quantitative results on synthetic data show the performances of the proposed method compared to well-established and state-of-the-art methods. Results on real images demonstrate that the proposed method is able to preserve accurately edges and structural details of the image [4]. Sten Roar Snare, Hans Torp, Fredrik Orderud, Bjorn Olav Haugen, have proposed a novel method for assisting no expert users in capturing the apical 4-chamber view in echocardiography has been presented. A Wilcoxon signed pair rank test yielded a statistically significant improvement of the view quality [6]. Roberto M. Lang, Luigi P. Badano, Victor MorAvi, have proposed a technique to updated normal values for all four cardiac chambers. This document provides updated normal values for all four cardiac chambers, including three dimensional echocardiography and myocardial deformation, when possible, on the basis of considerably larger numbers of normal subjects, compiled from multiple databases. In addition, this document attempts to eliminate several minor discrepancies that existed between previously published guidelines [9]. Georey E. Hinton and Vinod Nair have shown how to create a more powerful type of hidden unit for an RBM by tying the weights and biases of an infinite set of binary units, then approximated these stepped sigmoid units with noisy rectified linear units and showed that they work better than binary hidden units for recognizing objects and comparing faces. They also showed that they can deal with large intensity variations much more naturally than binary units [7].

Proposed Methodology

To improve the quality of echocardiograms, this paper has implemented Computational Neural Network.

A. Convolutional Neural Networks

The regression model was designed on a deep neural network architecture, structured in two main stages: a convolutional stage and a fully-connected stage. The first stage is composed of convolutional layers (conv) and pooling layers (pool); the second stage only contains fully-connected layers (fc).

B. Convolutional stage:

The conv layer, is the primary component of this stage. It consists of 2D kernels that are convolved with the input signal resulting in the output feature-maps. Mathematically, kernels calculate the locally weighted sum of inputs or, as the name implies, perform a discrete convolution, each kernel is convolved with all the feature-maps of the previous layer and generates a 2D output. Outputs of all kernels of a given layer are stacked together to create the 3D output feature-map of the conv layer. The total number of parameters in the conv layer is equal to the number of kernels multiplied by the size of each kernel.

Fully connected stage:

Each neuron in this layer is fully connected to every activation of its previous layer. Like conv layers, the output of an fc layer is also passed into an activation function. The output of the last fc layer is not filtered by an activation function as it produces the network's final output.

C. Framework

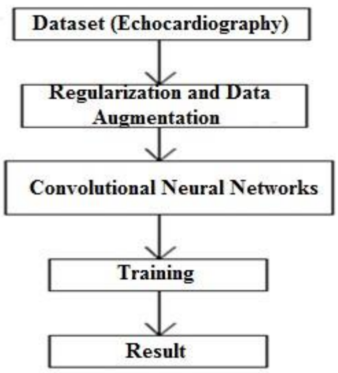

Fig. 1. Framework of CNN

The framework of this system consists of the following steps:

1) Dataset (Echocardiography): The dataset is fed into the system. This dataset contains echocardiography images of 6,916 patients who are previously diagnosed i.e. their decision tend to be true.

2) Regularization and data augmentation: To stabilize learning and prevent the model from over-fitting on the training data, several strategies were used. Regularization is a machine learning technique that adds a penalty term to the loss function to prevent the coefficients (weights) from getting too large.

3) Convolutional Neural Network: After the data regularization, the resultant data is passed to the processing unit where the algorithm is implemented on the data. We have processed the data in convolutional neural network. This data is classified into several decision as to which part of the four chambers need to be treated. After the classification is done, a new image is fed into the processing unit where the image is tested against the classified data.

4) According to the pattern matched in the classified data, an output is generated and gives result as to which part of the heart need a high attention.

D. Algorithm Notations:

W: input volume size

F: receptive field size of the Conv Layer

S: stride

P: amount of zero padding used W, H, D: width, height and depth *Algorithm:*

a) The Convolutional Layer:

The Conv layer is the core building block of a Convolutional Network that does most of the computational heavy lifting. To summarize, the Conv Layer: •Accepts a volume of size W1×H1×D1

•Requires four hyper parameters: Number of filters K, their spatial extent F, the stride S, the amount of zero padding P.

•Produces a volume of size W2×H2×D2 where: W2= (W1−F+2P)/S+1, H2= (H1−F+2P)/S+1 (i.e. width and height are computed equally by symmetry), D2=K

•With parameter sharing, it introduces F·F·D1 weights per filter, for a total of (F·F·D1) ·K weights and K biases.

b) Pooling Layer:

Its function is to progressively reduce the spatial size of the representation to reduce the number of parameters and computation in the network, and hence to also control over fitting. More generally, the pooling layer:

•Accepts a volume of size W1×H1×D1

•Requires two hyper parameters: their spatial extent F, the stride S,

•Produces a volume of size W2×H2×D2 where: W2= (W1−F)/S+1, H2= (H1−F)/S+1, D2=D1

•Introduces zero parameters since it computes a fixed function of the input

•Note that it is not common to use zero-padding for pooling layers.

It is worth noting that there are only two commonly seen variations of the max pooling layer found in practice: A pooling layer with F=3, S=2 (also called overlapping pooling), and more commonly F=2, S=2. Pooling sizes with larger receptive fields are too destructive.

c) Convolutional Neural Networks Algorithm:

In this research Amir H. Abdi, Christina Luong, have proposed CNN algorithm is used to detect the disease from given ECG image. We have used three layers of the CNN these are Convolutional Layer, Pooling Layer and fully connected layer. Here, convolutional layer and pooling layer, both layer work together. First it represents the image into three-dimension vector space then applies filters to convert that image into 2 dimensions. Again, fully connected layer applies the filters to recognize the image. After training the system when we pass the image to test it, as per the specified categories it classifies the image and detect the disease accurately. After disease detection system suggests the medicine on the detected disease. The Conv layer is the core building block of a Convolutional Network that does most of the computational heavy lifting. To summarize, the Conv Layer: •Accepts a volume of size W1×H1×D1

•Requires four hyper parameters: Number of filters K, their spatial extent F, the stride S, the amount of zero padding P.

•Produces a volume of size W2×H2×D2 where: W2= (W1−F+2P)/S+1, H2= (H1−F+2P)/S+1 (i.e. width and height are computed equally by symmetry), D2=K

•With parameter sharing, it introduces F·F·D1 weights per filter, for a total of (F·F·D1) ·K weights and K biases [11].

$$f_{fci}^{l}(a^{l-1}) = \sum_{j=1}^{n} W_{ij}^{l}\, a_j^{l-1} + b_i^{l}, \qquad (1)$$

TABLE I: Notations

Notations	Description
$ffcil$	Fully Connected.
$al{-}1$	Represents the input feature-map of the layer.
$w_i l$	Is the Weight matrix.
a_i^l	Output feature map of kernel.
b_i^l	Bias value.

d) Fully Connected Layer:

Output of pooling layer is the input of fully connected layer. Fully connected layer takes the output of polling layer and applies filer to recognize the object.

$$a_{i,jk}^{l}(a^{l-1}) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} W_{i,mn}^{l}\, a_{(j+m)(k-n)}^{l-1}, \qquad (2)$$

TABLE II: Notations

Notations	Description
$a_i l$	Output feature map of kernel.
w_i^l	Is the Weight matrix.
$al{-}1$	Represents the input feature-map of the layer.

Mathematical Model

Notations:

W: input volume size

F: receptive field size of the Conv Layer

S: stride

P: amount of zero padding used W, H, D: width, height and depth *Input:*

The input for this neural network are the images obtained from echocardiogram test.

Output:

To generate the final output we need to apply a fully connected layer to generate an output equal to the number of classes we need.

V. RESULT AND DISCUSSIONS

The designed model was trained three times on the training data and was evaluated on the test set against expert cardiologist's manual scores. The performances of the trained models were evaluated as the mean absolute error (MAE) Between the predicted AES and the expert's manual echo scores (MES).

Table I presents the performance of the three trained models for each quality-level as well as the overall accuracy of each model.

TABLE III: The performance of the three trained models on each quality-level and in total. Although their performances in each quality-level slightly varies, their overall accuracies match.

Model	**Mean Absolute Error(MAE)**						
	0	**1**	**2**	**3**	**4**	**5**	**Sum**
Model1	0.6	0.77	0.8	0.78	0.5	0.85	0.72
Model2	0.6	0.85	0.8	0.78	0.5	0.86	0.72
Model3	0.6	0.84	0.8	0.77	0.5	0.87	0.72
Avg. model	0.6	0.81	0.8	0.77	0.5	0.86	0.71

Conclusions

Propose approach provides framework for automatic quality assessment of echo data using convolutional neural network model. The goal of proposed technique is to improve echo by reducing observer variability in data acquisition using a realtime assessment mechanism that helps the operator to read just the probe and acquire an optimal echo. By minimizing operator dependency on echo acquisition and analysis, this research would lead to widespread use of echo at any point-of-care, hence it would enable early and timely diagnosis and treatment of high-risk patients with improved accuracy, quality assurance, workflow, and throughput

Acknowledgement

We are thankful to all the authorities of cPGCON for providing a platform to present our work. We express our deepest gratitude to the college authorities for technical guidance and infrastructure. Lastly, we wish to thank the researchers and reviewers for their contributions because of which we could complete this work.

References

[1] L. Lvstakken, F. Ordernd, and H. Torp, Real-time indication of acoustic window for phased-
Array transducers in ultrasound imaging, Proceedings of IEEE Ultrasonic Symposium, pp. 15491552, 2007.

[2] Automatic cardiac view classification of echocardiogram, Proceedings of the IEEE International Conference on Computer Vision, pp. 07, 2007. X. Glorot, A.
Bordes, and Y. Bengio, Deep Sparse Rectifier Neural Networks, Aistats, vol. 15, pp. 315323, 2011.

[3] H. Wu, D. M. Bowers, T. T. Huynh, and R. Souvenir, Echocardiogram view classification using low-level features, pp. 752755, April 2013.

[4] P. Coupe, P. Hellier, C. Kervrann, and C. Barillot, Nonlocal means based speckle filtering for ultrasound images,
IEEE Transactions on Image Processing, vol. 18, no. 10, pp. 22212229, 2009.

[5] V. Nair and G. E. Hinton, Rectified Linear Units Improve Restricted Boltzmann Machines, 27th International Conference on Machine Learning, pp. 807814, 2010.

[6] S. R. Snare, H. Torp, F. Orderud, and B. O. Haugen, Real-time scan assistant for echocardiography, IEEE Trans. Ultrasonic, Ferroelectrics, and Frequency Control, vol. 59, no. 3, pp. 583589, 2012.

[7] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, Dropout: A simple way to prevent neural networks from over fitting, Journal of Machine Learning Research, vol. 15, pp. 19291958, 2014.

[8] G. N. Balaji, T. S. Subashini, and N. Chidambaram, Automatic classification of cardiac views in echocardiogram using histogram and statistical features, Procedia Computer Science, vol. 46, no. Icict 2014, pp. 1569 1576, 2015.

[9] R. M. Lang , Recommendations for Cardiac Chamber Quantification by Echocardiography in Adults: An Update from the American Society of Echocardiography and the European Association of Cardiovascular Imaging, Journal of the American Society of Echocardiography, vol. 28, no. 1, pp. 139, aug 2016.

[10] X. Glorot, A. Bordes, and Y. Bengio, Deep Sparse Rectifier Neural Networks, Aistats, vol. 15, pp. 315323, 2011.

[11] Amir H. Abdi, Christina Luong, Teresa Tsang, Gregory Allan, Saman Nouranian, John Jue, Dale Hawley, Sarah Fleming, Ken Gin, Jody Swift, Robert Rohling, and
Purang Abolmaesumi, "Automatic Quality Assessment of Echocardiograms Using Convolutional Neural Networks: Feasibility on the Apical Four-chamber View". TMI.2017, IEEE Transactions on Medical Imaging.