Heart Compartment Obstacle Finding with the help of Image Processing

Saurabh Suryavanshi, Swarnima Lele, Sayali Pawar, Shubham Kondhare, V.S.Rajput

Abstract: Neural Network is one of the upcoming Concept that comprises of the concept similar to the human neural system. The basic idea in the neural network is the interaction between neurons and the hidden layer. The neurons communicate with the help of information networking done between them and the weight of it. The proposed system is the application of a neural network. The proposed system implements a Convolutional Neural Network in the medical field. The system consists of echocardiogram images that help to analyze the defect in the patient’s heart chambers. The images are captured with the help of ultrasound technique. The motto of the proposed system is to reduce the overhead of the cardiologist. According to the existing technologies available, the cardiologist or the experts require a certain amount of time to detect the exact defect in the heart chambers, but the system facilitates to accurate and immediate defect prediction. This approach considers the view of apical four-chamber (A4C) which considers 4 chambers of the heart. This is a powerful approach which can detect even a little defect in the heart which human eye tend to ignore.

Keywords: Convolutional neural network, Deep learning, Quality assessment, Echocardiography, Apical four-chamber.

Introduction:

Data mining is one of the domain that is gaining great amount of interest in this techno-savvy world. Data mining has numerous applications in different fields. The proposed paper focuses on data mining usage in the field of health-care. Data mining helps to predict various chronic disease on the basis of different input parameters. Our system performs prediction on the basis of input images of heart chambers captured with the help of ultrasound technique. Till date the disease prediction is done manually, which takes certain amount of time for detection and may consist of some flaws in it. Any time of error in disease prediction adversely affects the health (life) of a patient’s which ultimately results into degradation of survival rate. Thus, to overcome this disadvantage the proposed system automatically detects the defect in the heart chambers in negligible amount of time and with more accuracy. The prediction is done without any human interference and thus has less chances of error in the prediction. The accuracy of estimations of chamber volumes, function and ejection fraction in 2D echo views, such as the A4C view, depend on the quality of the acquired cine. To assist the sonographer in acquiring optimal views, several research groups have made notable efforts in producing real time feedback to the operator regarding image quality. A set of studies have attempted to detect shadows and aperture blockage in echo images. Several groups have proposed content-based cardiac interview classification techniques using machine learning and statistical approaches as well as low-level features. However, intra-view quality analysis of echo is a much more challenging problem, as there is relatively higher correlation between the visual content of the different echo images that need scoring. 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. This paper has demonstrated the feasibility of our approach on the A4C echo view. Using GPU-computing, the ultimate trained network is able to assess the quality of an echo image in real time. Since the design of the proposed DCNN architecture does not include any a priori assumptions on the A4C view, this approach could be extensible to other standard echo views.

Related work:

Lasse Løvstakken 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 do 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. Automatic Quality Assessment of Echocardiograms Using Convolutional Neural Networks: Feasibility on the Apical Four-chamber View

To The previous regression model follows the standard deep convolutional neural network architecture, with adequate parameters to learn complex feature representations of echo images from thousands of training samples. The design is composed of convolutional layers (conv), max-pooling layers (pool) and fully-connected layers (fc). [1].

2. Echocardiogram View Classification using Edge Filtered Scale-invariant MotionFeatures.

In this sheme present a system for automatic view classification that exploits cues from both cardiac structure and motion in echocardiogram videos. [2] In this framework, each image from the echocardiogram video is represented by a set of novel salient features. It is locate these features at scale invariant points in the edge-filtered motion magnitude images and encode them using local spatial, textural and kinetic information.
3. Real-time Indication of Acoustic Window for Phased-Array Transducers in Ultrasound Imaging

The acoustic contact or window in phased-array imaging can be estimated directly through spectral analysis of the received signal in real-time. The bandwidth of the lateral spectrum closely corresponded to the effective imaging aperture in phantom recordings for different degrees of acoustic contact, and further indicated the loss in acoustic contact due to the human sternum in real-time cardiac imaging. [3].

4. Real-Time Scan Assistant for Echocardiography

A real-time scan assistant (SA) for use with echocardiography is presented. [4] The motivation is to aid non-expert users in capturing apical 4-chamber views (A4CH) during echocardiography.

5. Automatic classification of cardiac views in echocardiogram using histogram and statistical features.

In this paper, we developed an automatic system for cardiac view classification of echocardiogram. This system is built based on the data-driven machine learning techniques along with two key approaches. [5] The first is to incorporate the local information (LV structure) and global information (global view by anchoring the LV structure).

6. Dropout: A simple way to prevent neural networks from over fitting

Dropout is a technique for improving neural networks by reducing over fitting. Standard back propagation learning builds up brittle co-adaptations that work for the training data but do not generalize to unseen data.


This paper explores sequential optimization strategies for hyper-parameter optimization for these two datasets: convex and MRBI. [7] The question of “How well does a DBN do on the convex task?” is not a fully specified.


This paper shows that networks of rectifying neurons yield equal or better performance than hyperbolic tangent networks in spite of the hard non-linearity and non-differentiability at zero and create sparse representations with true zeros which are remarkably suitable for naturally sparse data. [8]

9. Rectified Linear Units Improve Restricted Boltzmann Machines.

This paper shows that ReLUs work better than binary hidden units for several different tasks. [9] Results are worse than that of Convolutional nets.


This system we developed a nonlocal (NL)-means-based filter for ultrasound images by introducing the Pearson distance as a relevant criterion for patch comparison. Experiments were carried out on synthetic images with different simulations of speckle. During the experiments, quantitative measures were used to compare several denoising filters.

Motivation:

System Architecture:

The main motive of this system is to predict the defect in a cardiac arrest patient. This is done by processing the echocardiogram images. An echocardiogram is one kind of ultrasound test that uses high-pitched sound waves that are sent through a device called a transducer. But the quality of an echocardiogram image cannot be guaranteed to be good. It may also contain some distractions. Our enhanced approach will make sure that the echocardiogram images trained by Convolutional Neural Network should have less error for the algorithm to find the defect. To achieve this, we could start improving our neural network by adding some pooling layers in between them so that the more features are extracted from it. Also, minimum errors can be achieved by padding the spatial arrangement by zeros. This will help retaining image’s actual size. This is helpful for preserving the image size which will recall the quality of the image. After the patient’s defect has been discovered, our next contribution is to recommend the diagnosis of the patient. Meaning, the system will recommend the health risks and diagnosis methods for further treatment. For example, if the system detects the defect in Left Artery then this system will recommend the relevant disease and diagnosis methods for treating that disease.
<table>
<thead>
<tr>
<th>Notations</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_i^l$</td>
<td>output feature map of kernel.</td>
</tr>
<tr>
<td>$w_i^l$</td>
<td>Is the Weight matrix.</td>
</tr>
<tr>
<td>$a^{l-1}$</td>
<td>Represents the input feature-map of the layer.</td>
</tr>
<tr>
<td>$f_{fc}^l$</td>
<td>Fully Connected.</td>
</tr>
<tr>
<td>$a_i^{l-1}$</td>
<td>Represents the input feature-map of the layer.</td>
</tr>
<tr>
<td>$w_i^l$</td>
<td>Is the Weight matrix.</td>
</tr>
<tr>
<td>$a_i^l$</td>
<td>output feature map of kernel.</td>
</tr>
<tr>
<td>$b_i^l$</td>
<td>Bias value.</td>
</tr>
</tbody>
</table>

1) Convolutional Stage

The Conv layer is the core building block of a Convolutional Network that does most of the computational heavy lifting. 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 overfitting.

$$a_{i,j,k}^l = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} w_{i,m,n}^l a_{(j+m),(k+n)}^{l-1}.$$

2) 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.

$$f_{fc}^l(a^{l-1}) = \sum_{j=1}^{n} w_{i,j}^l a_{j}^{l-1} + b_i^l.$$

System Analysis:

Fig 1 shows the details system of echocardiogram, in that user is first 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. 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. Convolutional Neural Network: After the data regularization, the resultant data is passed to the processing unit where the algorithm is implemented on the data. They 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. 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.
Conclusion:
This paper has worked on giving an immediate feedback on echocardiogram result. To provide such feedback, this paper has proposed a framework for automatic quality assessment of echo data. They have taken the advantage of a large dataset of 6,916 A4C images to design, optimize and train our deep neural network model. The result showed a mean absolute error of 0.71, which is in the same order as the intra-rater reliability of the expert. The three trained models which was used in here, demonstrate a mean absolute error of 0.72 and exhibit almost the same performance on each quality level. This is an indication of the independence of the results from the random weight initializations in conv and fc layers, random mini-batch selection, random data augmentation, and random dropout of

References:

