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Automatic Quality Assessment of Apical Four-Chamber Echocardiograms using Deep Convolutional Neural Networks

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Abstract: Neural network has been evolving day by day with many features. The core of the neural network lies in the interaction between the neurons in the hid- den layer. The neurons interact with each other by considering the weights between them. This results in the output of the system. There are many applications in which neural network can be practiced. This paper proposes Convolutional Neural Networks in medical science. It focuses on echocardiography. The term echocardiography means that the internal structure of a patient's heart is studied through the images. The ultrasound waves create these images. The abnormalities in these images are found through echo. The motive of this work is to decrease the overhead of the cardiologist. This approach will result in pointing the abnormality in the heart. Since, cardiologist and less experienced surgeons may take a while to figure out the defect or may miss the defect in the heart. This approach considers the view of apical four-chamber (A4C) which considers 4 chambers of heart. This is a powerful approach which can detect even a little defect in heart which human eye tends to ignore.
Keywords: Convolutional neural network, Deep learning, Quality assessment, Echocardiography, Apical four-chamber.

I. INTRODUCTION

This Data mining has been gaining numerous number of eye consideration in the past decades. Data mining has proved to be very effective in many fields. This paper has focused on a very popular field i.e. healthcare field where data mining has served many applications. One of the applications in healthcare field is predicting the disease through some parameters which will be useful in decision making before diagnosis. This can save a good amount of life since the decision to be taken for diagnosis should be fast. But what if the decision in incorrect and contain some error? This kind of false decision for diagnosis can take a life out of a person. To avoid such kind of risk we need to make a system which can be reliable and in which the doctor can easily trust. This paper has focused on echocardiography where the decisions to detect the defect in the four chambers of heart quick. The accuracy of estimations of chamber volumes, function and ejection fraction in 2D echo views, such as the A4C view, depends 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. In this study, data acquired from 6,916 patient studies were used to design, optimize, train and test the model. 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.

II. LITERATURE REVIEW

A. Lasse Lvstakken and Fredrik Ordered 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 helping ensure that a good image quality is obtained in contexts where the acoustic contactor 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.

B. J. H. Park1, S. K. Zhou have proposed a fully automatic system for cardiac view classification of echocardiogram. Given an echo study video sequence, the system outputs a view label among the pre-defined standard views. The system is built based on a machine learning approach that extracts knowledge from an annotated database. It characterizes three features: 1) integrating local and global evidence, 2) utilizing view specific knowledge, and 3) employing a multi-class Logit-boost algorithm. In this prototype system, they classify four standard cardiac views: apical four chambers and apical two chambers, parasternal long axis and parasternal short axis (at mid cavity). Proposed method helps to achieve classification accuracy over 96% both of training and test data sets and the system runs in a second in the environment of Pentium 4 PC with 3.4GHz CPU and 1.5G RAM.

III. PROPOSED SYSTEM

A. Introduction

CNN as you can now see is composed of various convolutional and pooling layers. Let's see how the network looks like.

1) We pass an input echocardiogram image to the first convolutional layer. Convolution layer extract relevant feature from the input image to pass further.
2) Each filter shall give a different feature to aid the correct class prediction .in case we need to retain the size of the image, we use same padding (zero padding), and otherwise valid padding is used since it helps to reduce the number of feature.
3) Pooling layers are then added to further reduce the number of parameters.
4) Several convolution and pooling layers are added before the predictions made**.** Convolutional layer help in extracting features. As we go deeper in the network more specific features are extracted as compared to a shallow network where the features extracted are more generic.
5) The output layer in a CNN as mentioned previously is a fully connected layer, where the input from the other layers is flattened and sent so as the transform the output into the number of classes as desired by the network.
6) The output is then generated through the output layer and is compared to the output layer for error generation. A loss function is defined in the fully connected output layer to compute the mean square loss. The gradient of error is then calculated.

B. System Architecture

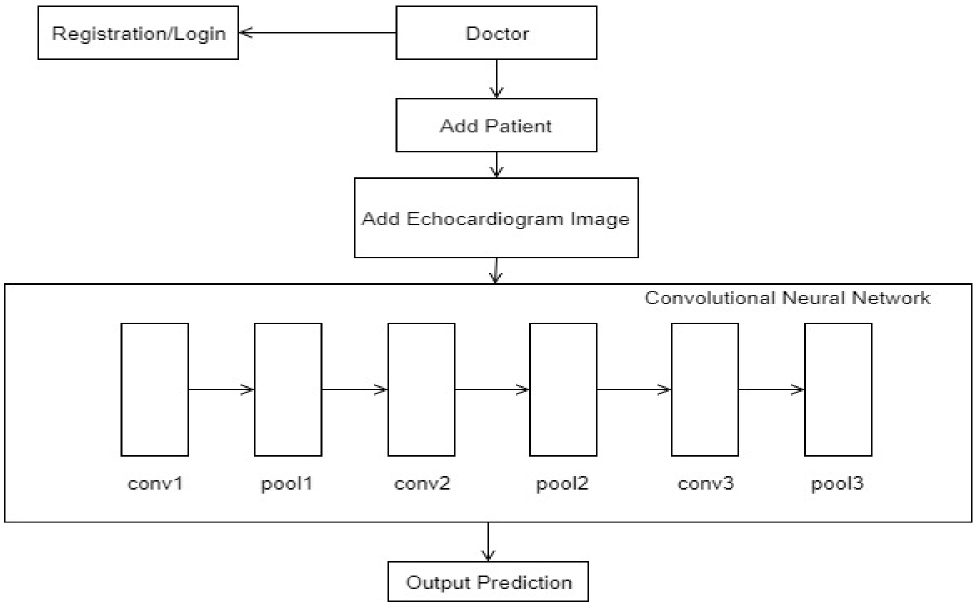

Fig. 1 System Architecture

C. Solving Approach

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. They have processed the data in convolutional neural network. This data is classified into several decisions 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.

IV. CONCLUSIONS AND FUTURE

This project 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 of0.71, 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 con v and fc layers, random mini-batch selection, random data augmentation, and random dropout of units during training.

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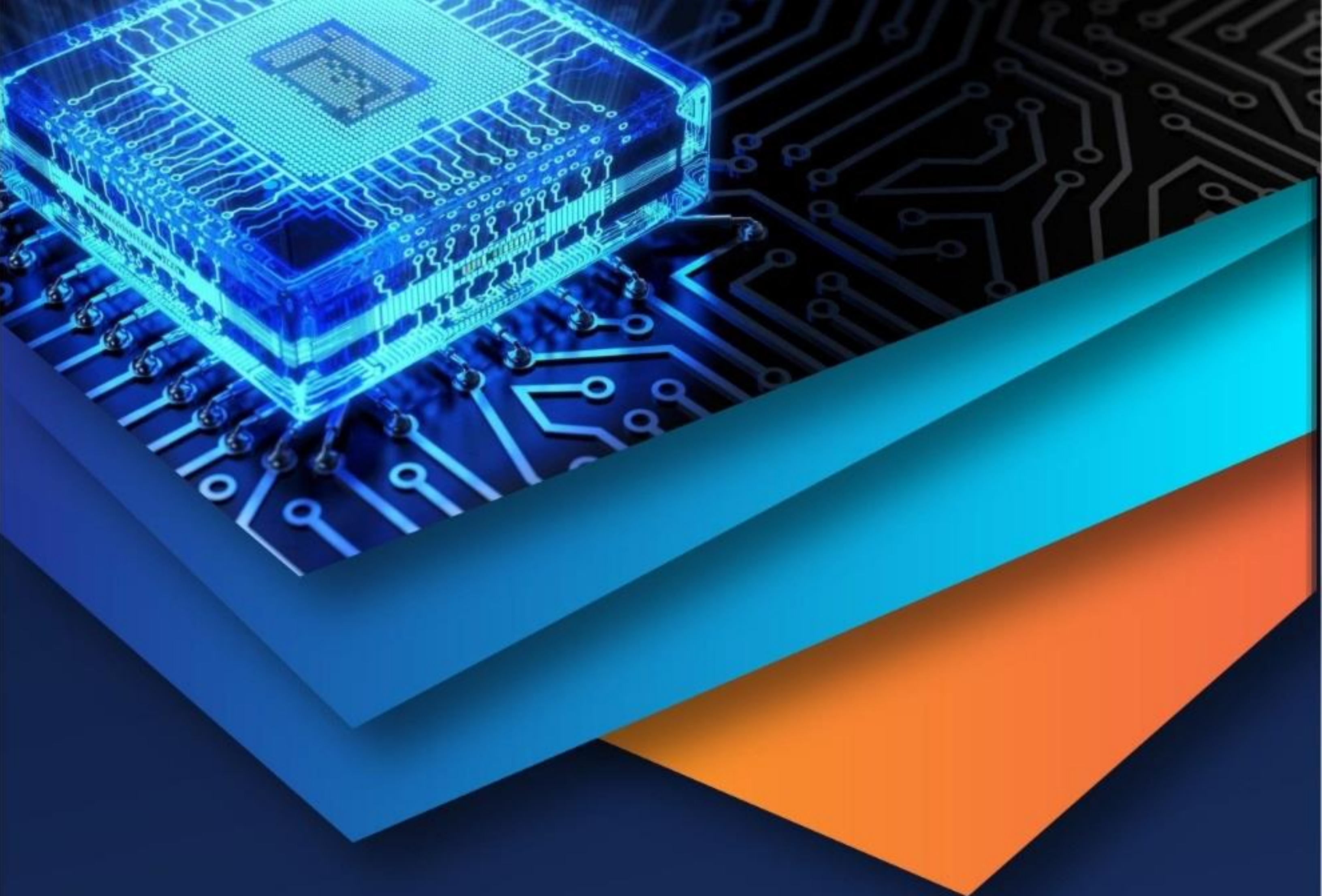

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