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Convolutional Neural Networks for the Assessment of Fetal Echocardiography

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Abstract

Fetal echocardiography is a standard diagnostic tool used in the evaluation and monitoring of fetuses with a compromised cardiovascular system associated with several fetal conditions. Convolutional neural network (CNN) is a computer technology which can perform specific tasks with specific goals. In this study we have used deep learning techniques to evaluate fetal cardiac ultrasound images and improve the evaluation of fetal abnormalities. In this study, we implemented convolutional neural network (CNN), a deep learning algorithm for the processing and classification of ultrasonographic images into various classes. The tool we used was able to sort the fetal cardiac images into 5 standard view with 97.47% accuracy. Further, it was able to diagnose Tricuspid Atresia and HLHS with an accuracy of 84.68%. This deep learning based algorithm was an efficient tool for evaluation and monitoring of normal and abnormal fetal heart images.

Keywords

Fetal echocardiography; Congenital Heart Defect(CHD); Deep learning; Convolutional neural network(CNN); Tricuspid Atresia(TA); Hypoplastic Left Heart Syndrome(HLHS)

1. Introduction

Imaging is a major part of medical diagnosis. Interpreting medical images requires extensive training and practice and is a complex and time-intensive process. Deep learning, specifically convolutional neural networks (CNN)[1], is a machine learning technique that learns patterns in images. It has shown good performance at helping experts with image-based diagnosis in radiology, pathology and classifying images of benign vs. malignant lesions[2, 3].

Congenital heart disease (CHD) is a birth defect affecting 1% percent of live births [4, 5, 6]. CHD may be asymptomatic in the intrauterine period but cause substantial morbidity and mortality after birth. Early diagnosis of CHD enables better outcomes and therapeutic options at birth[4, 5, 7]. Deep learning has not yet been widely applied to fetal echocardiography (detailed study of fetal heart).

The main reason for this startling diagnosis gap is inadequate/uneven expertise in interpreting fetal cardiac images, due to the diagnostic challenge presented by a small and fast-beating fetal heart and due to relatively low exposure to congenital heart disease among caregivers (owing to its low prevalence). Small, single-center clinical quality control programs can increase detection of CHD up to 100 percent, but such programs are difficult to sustain and scale. So, deep-learning image analysis has been implemented to improve the diagnostic rates commonly encountered in community practice. This result has been obtained even when trained only on a relatively small number of clinically relevant imaging.

The detection rate of CHD can be increased substantially by small, single-center clinical quality control programs but such programs are difficult to sustain and scale. Therefore, this study aims to test whether CNN in spatial image analysis could improve upon diagnostic rates commonly encountered in community practice, even when trained on relatively small number of clinically relevant imaging studies [5, 8]. The objective of this study was to identify and predict the five standard views of fetal heart used in the antenatal ultra-sonographic study of fetal heart and to demonstrate a deep learning based image classification tool for prediction of common CHD lesions in particular Tricuspid atresia (TA) and Hypoplastic left heart syndrome (HLHS).

2. Methodology

The deep learning technique has been used for the purpose of canonical screening of fetal heart. Figure 1 illustrated the overall system for fetal cardiac images identification and classification along with the prediction of common CHD lesions.

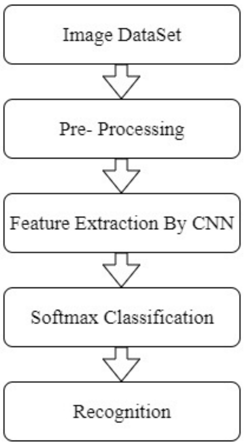

Figure 1: System Block Diagram for fetal heart image classification

2.1 Dataset Collection and Description

In this study, five canonical screening views of fetal heart Ultrasound data will be used to diagnose the fetal health. With waived consent, all data is de-identified to maintain the privacy of the person. Dataset will be divided into training, testing and validation. The image dataset used is Labelled Images.

It contains 9666 images of 5 different standard views of fetal heart and 4407 of CHD lesions Ultrasound data collected from multiple centers in Kathmandu (Nepal) and Bhubaneshwar (India). Altogether 5969 images of five standard views of fetal heart are used for training and 2000images are used for validation and 1697 images are used to test the model.

Similarly, 2206 images are used for training CHD, 1000 images are used for validation and 1201 images are used for testing.

2.2 Image preprocessing

The network architecture as well as the input data format must be carefully considered when constructing an efficient neural network model. The common parameters are the number of pictures, picture height, picture width and number of channels.

All the images from different source including RGB images have been converted to gray scale images (size - 150 X 150). Histogram equalization technique is used to improve the contrast in images by stretching out the intensity range. This process is followed by image augmentation. Before resizing the image, the region of interest according to five standard views has been segmented using a pre-built model[6][12].

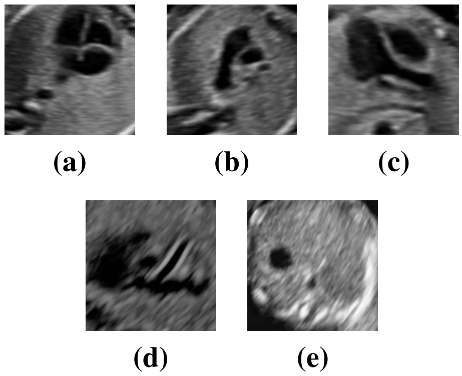

Figure 2: Five standard views of fetal heart **(a)** Four Chamber (4Chamber) **(b)** Three Vessel View (3VV) **(c)** Left Ventricular Outflow Tract(LVOT) **(d)** Right Ventricular Outflow Tract(RVOT) **(e)** Abdominal(ABDO)

2.3 Five View Classification

CNNs are great at finding patterns and using them to classify images. They are made up of numerous hidden layers. It comprises of filters or kernels or neurons that have learnable weights, parameters and. Each channel takes a few inputs and does convolution(Figure 3) . The components of CNN comprise of :

2.3.1 Convolutional Layer

Convolution layer will calculate the output of the neurons that depends only on a small number of inputs, each computing a dot product between a small number of inputs and their corresponding weights. This layer is the center building block of a CNN that performs most of the computational calculations. Its main function is feature extraction. It retains the spatial relation between pixel from input image. This results in activation map and fed as input data to the next layer. The 1st convolutional layer has 32 filters, while 2nd has 64, 3rd has 128, 4th has 64 and finally 5th has 32 filters for feature extraction.

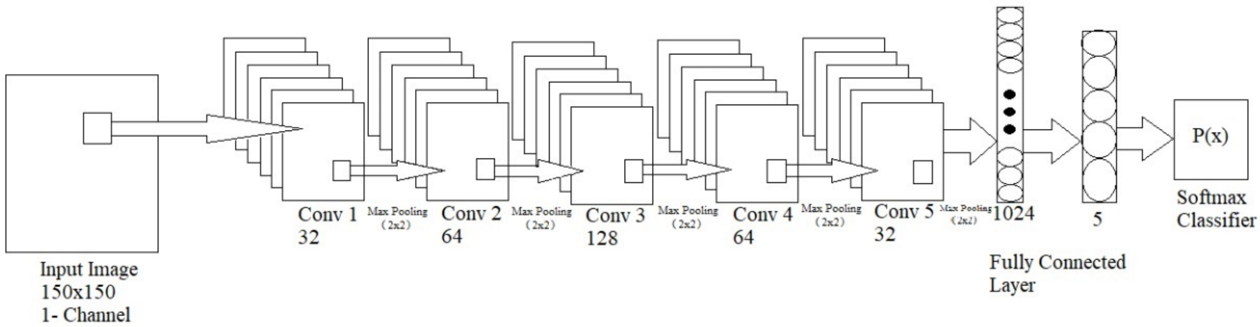

Figure 3: CNN architecture for standard five view classification of fetal heart

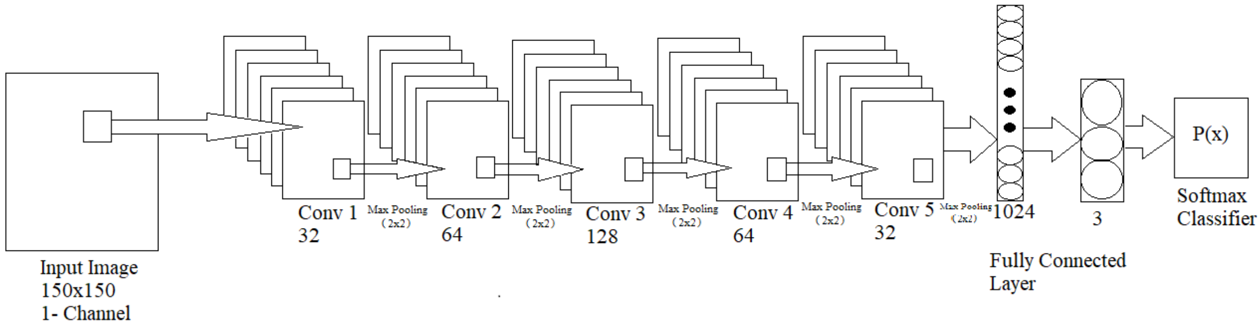

Figure 4: CNN architecture for Normal vs CHD lesions.

2.3.2 Activation function

Activation function has ability to add non-linearity in the network in order to learn complex patterns in the data. It converts output from the previous cell into some other form that can be used as the input to the next cell. The most commonly used activation function in CNN is ReLU. It is a component wise operation that reconstitutes all negative values within the highlight outline by zero. In arrange to know how the ReLU works, we accept there's a neuron input given as x and from the rectifier[14]. It is defined as R(z) = max (0, z), is not differentiable at z = 0.

2.3.3 Pooling Layer

Convolution neural network often use pooling layer to reduce the size of the representation for faster computation as well as make some of the features that detects a bit more robust [15]. It is applied to shrink the stack of the image. To design pooling layer, we need hyper parameters as filter size and stride. Here, Max Pooling has kernel size 2 and stride 2.

2.3.4 Fully Connected Layer

Classification of data into various classes can be done using fully connected neural network. The main function of the fully connected layer is to take the input from last convolution layer or pooling layer and use the to classify the given image into its corresponding label. In this layers, the input from the previous layer are connected to each activation unit of the next layer[16][9]. The fully connected layer has five nodes for classification of five different views of fetal heart. Softmax is an activation function often used to classify multiclass problem. The output of Softmax gives the name of five different standard view of fetal heart

2.4 Diagnosis of Normal vs CHD lesions

For detection of normal Heart Vs CHD lesions[1][9],a similar model is used as it was used in the case of standard five view classification with some modifications. The CNN architecture for this diagnostic model is shown in Figure 4.

3. Results and Discussion

A fully functional view classification of canonical views of fetal heart recognition system has been developed. The system is able to classify the five different standard views of fetal heart images with an accuracy of 97.45% on 7969 train/validation data and 1697 test data.

3.1 Five View Classification and Performance Evaluation

A fully functional model to classify the fetal cardiac images into five standard views has been developed. It was able to classify the images with 97.45% accuracy on 5969 training images with 2000 validation samples as shown in Figure 5.

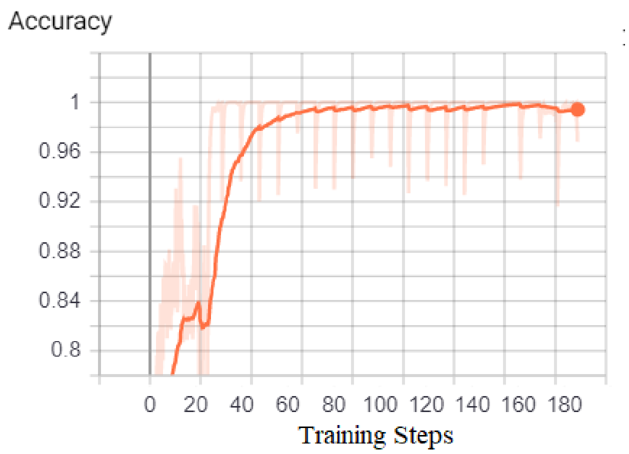

Figure 5: Training Accuracy Vs Training Steps

The confusion matrix Figure 6 for five standard views classifier. This is used to describe the performance of a classifier on 1697 test samples whose actual values are already known. It addresses the class imbalance problem.

The trained model will do predictions on the test data. Based on the predictions, the confusion matrix parameters are calculated as true positives, true negatives, false positives and false negatives. The CNN model for five standard views classifier predicts with an accuracy of 97.47%.

Table 1 shows the calculation and distribution of evaluation matrix for five standard fetal cardiac images with their corresponding values

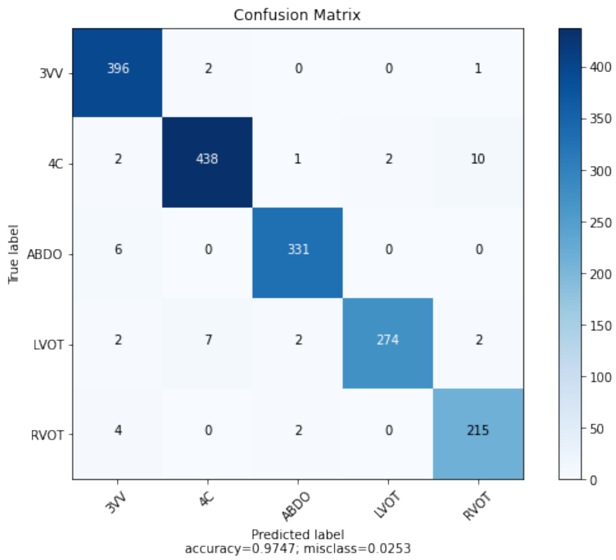

Figure 6: Confusion matrix of the five standard views of fetal heart

3.2 Normal Heart Vs Congenital Heart Disease(CHD) Classification and Performance Evaluation

A fully functional model to classify the Normal heart vs CHD has been developed. It was able to classify the images with 94.29% accuracy on 5969 training images with 2000 validation samples.

Figure 7 shows a plot of accuracy along the y-axis and number of training steps along the x-axis. The accuracy of the training showed a steep increase from start of step to 80t̂h steps and then plateaus. The final value reached to 94.29% at the last trainnig step.Hence, model performance was improving over time, which means the model was learning.

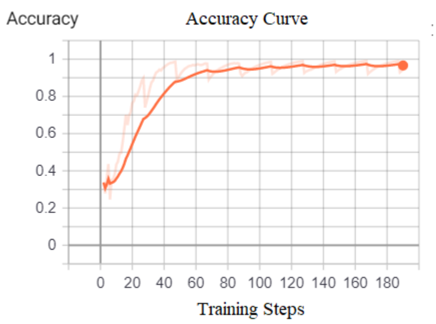

Figure 7: Training Accuracy Vs Training Steps

Figure 8 shows the confusion matrix for five standard views classifier. This is used to describe the performance of a classifier on 1201 test samples

Table 1: Performance Evaluation metrics for five Views of fetal heart

	Labels	True Positives	True Negatives	False Positives	False Negatives	Accuracy	Precision	Recall	Specificity	F1 Score
0	3VV	396	1284	14	3	0.989982	0.965854	0.992481	0.989214	0.978986
1	4C	438	1235	9	15	0.985857	0.979866	0.966887	0.992765	0.973333
2	ABDO	331	1355	5	6	0.993518	0.985119	0.982196	0.996324	0.983655
3	LVOT	274	1408	2	13	0.991161	0.992754	0.954704	0.998582	0.973357
4	RVOT	215	1463	13	6	0.988804	0.942982	0.972851	0.991192	0.957684

Table 2: Performance evaluation matrics parameters for normal heart vs CHD lesions

	Labels	True Positives	True Negatives	False Positives	False Negatives	Accuracy	Precision	Recall	Specificity	F1 Score
0	HLHS	253	771	0	177	0.852623	1.000000	0.588372	1.000000	0.740849
1	Normal4C	613	404	184	0	0.846794	0.769134	1.000000	0.687075	0.869504
2	TA	151	1043	0	7	0.994172	1.000000	0.955696	1.000000	0.977346

whose actual values are already known. It addresses the class imbalance problem.

The rows of confusion matrix represents the true labels and columns represents the predicted labels as shown in Figure 8. The trained model will do predictions on the test data. Based on the predictions, the confusion matrix parameters are calculated as true positives, true negatives, false positives and false negatives. In this classifier, the model predicts with an accuracy of 84.68%.

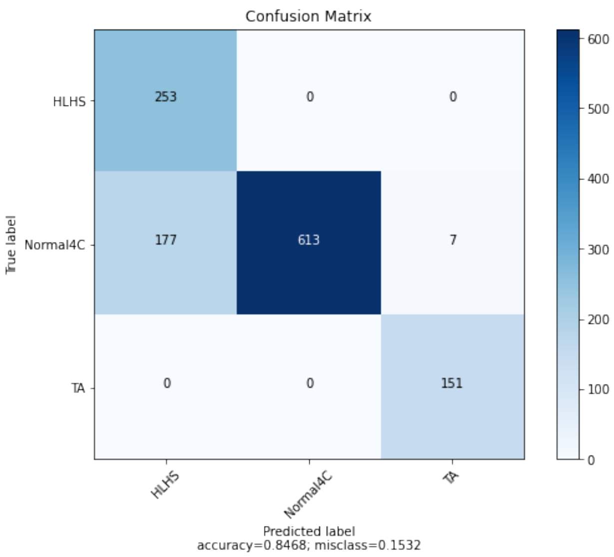

Figure 8: Normal heart vs CHD lesions Confusion Matrix

Table 2 shows the calculation and distribution of evaluation matrix for five standard fetal cardiac images with their corresponding values.

4. Conclusion

Hence, Convolution Neural Network (CNN), a deep learning tool was able to classify the fetal cardiac images into the five standard views with 97.47% accuracy. Similarly, CNN correctly identified and diagnosed Tricuspid Atresia (TA) and Hypoplastic left heart syndrome (HLHS) with testing accuracy of 84.68%.

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