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Detecting Abnormalities of Fetal Cardiac Using Deep Learning in Parallel Computing Environment

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Abstract: Deep learning has become a recent explosion in our everyday lives. Being one of the leading machine learning tools among various tools, deep learning contributes a lot to image analysis and the vision of the computer. This tool is considered enormous for image analysis, especially in detecting fetal cardiac abnormalities in a parallel computing environment. Screening congenital cardiac disease (CCD) is challenging in achieving accuracy in terms of diagnoses concerning the manual process. Hence in this proposed work, optimized ultrasound image (USI) based Artificial Neural Network (ANN), a deep learning tool, has proven in exploiting the dissimilitude prognoses of cardiomyopathies and in predicting perinatal mortality of congenital cardiac disease (CCD). Fetal Cardiac parameters are evaluated using the myocardial performance index (MPI), a biomarker of global cardiac function providing statistics on various periods during diastolic and systolic phases. This paper also discusses some potential trends of deep learning application in ultrasound image analysis in detecting and predicting the abnormalities in fetal cardiac function.

Keywords: Fetal Cardiac, Deep Learning, Artificial neural network, detection, Parallel Computing.

1. Introduction

Fetal cardiac with ultrasound have made detection of abnormalities easier. Congenital cardiac diseases (CCD) are common faults in nearly 0.8% of the world's population [1]. The most common defects are septal and hole positions occurring in various places [2-4]. It has become easy to screen CCD of fetal during the prenatal ultrasound observation. This US device is very affordable cost with radiation-free imaging that helps diagnose the CCDs. [5,6]. Diagnosing abnormalities with fetal ultrasound (US) has become a challenging task due to the blurry images the reduces and corrupt the quality of the image [7,8] In recent trends, fetal cardiology is Deep learning, one of the machine learning branches, is a learning approach that process directly high level

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and middle level from the Ultrasound raw data. Convolution neural network is a deep learning method worn the visual recognition challenge [9]. Today, deep learning has occupied a great position in network models like neural architectures and generative techniques [10]. The proposed model deals with the deep learning technique to detect the abnormalities in fetal cardiac function under a parallel computing environment.

2 Proposed Methodology

Cardiac diagnosis of fetal abnormalities has been stimulated by the USI technology and the advances with deep learning in a parallel computing environment. Deep learning algorithms have been exploited in various medical applications, especially in fetal US technology, predicting perinatal outcomes or detecting preterm births [11,12]. The proposed model is performed in Four phases. USI-based optimal ANN is a state-of-the-art model for the segmentation and detection of fetal cardiac abnormalities. Data Acquisition, Preprocessing, Segmentation, Detection and Parameter evaluation. Fetal ultrasound images are fed to the input layer to the Deep learning model. Image framing and resizing are carried out during data imputation in preprocessing phase. In the third phase, segmentation and detection phases are undertaken under a parallel computing environment where the resized images are segmented using USI-based optimal ANN architecture. The performance analysis uses the evaluation metrics with myocardial performance index (MPI) and M mode metrics shown in **Figure 1**.

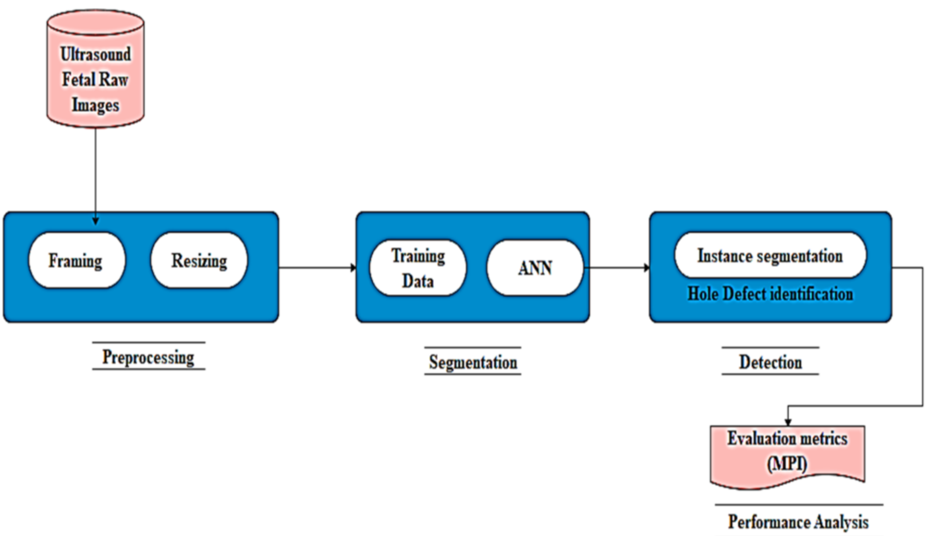

Figure 1. Proposed Architecture of Fetal Cardiac Detection

The artificial neural network creates space for input resized images. This ANN predicts the class of the object refining the hidden layers at two stages. The feed-forward techniques extract features from the raw images producing a mapping function between two corresponding levels of the two pathways. The process of ANN consists of a feature extractor with the region. It processes extracts high-level features from the raw frames [**Figure 2**]. Such frames help the cardiologist distinguish the fetal cardiac region through manual segmentation. Segmentation and detection is a two-stage process that performs the multi-task losses in the parallel computing environment. The loss function in the detection phase is given by

$$L_f(\{p_r\},\{V_i\}) = \sum_{i=0}^{n} \quad LiLsL_l\,(p_r,p_g) \tag{1}$$

Where p_r is the prediction probability of the ith image and p_g is the ground truth value of one of the images is positive and 0 if the image is negative and V_i is the vector representing the image coordinates of the ground truth box that refers to the given image. L_l as the log loss function. In addition, the multiple task loss of USI based ANN is defined as LS:

$$LS = L_{cl} + L_r + L_i \tag{2}$$

Where $L_{cl}$the loss of classifying fetal cardiac in ANN is, L_r is considered as regression loss and L_i is the hidden loss. Thus, sigmoid function can be implied per pixel with entropy hidden loss and class LS. In the proposed architecture, all the input images are of the same size or rescaled to 512 x 512 pixels with the network. Fetal cardiac ultrasound images are segmented into nine sequential methods for analysis that includes transverse phase, four-chamber heart phase, left ventricular and right ventricular outflow tract phase, three vascular tracheal and bilateral artery phases, the long axis with various arterial phase portrayed in **Figure 3**

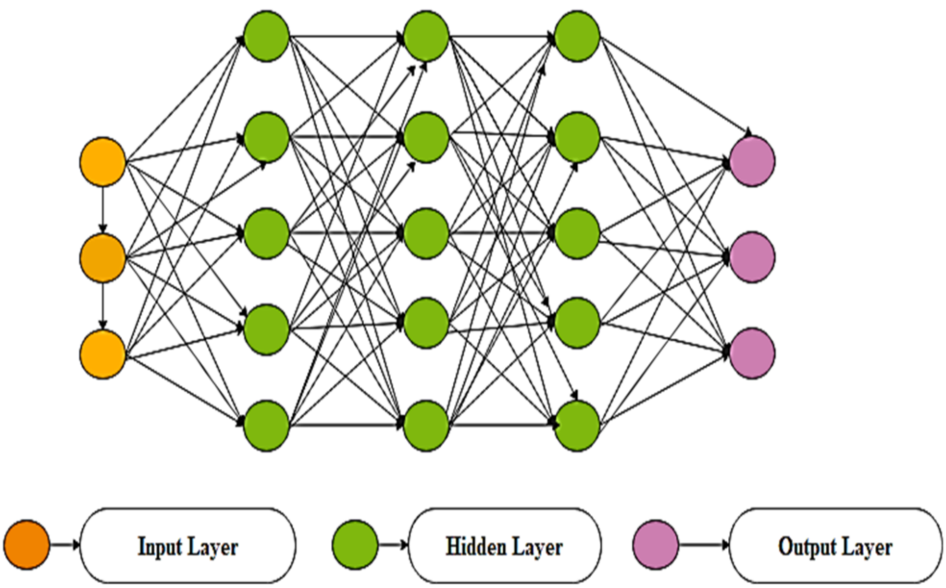

Figure 2. Artificial Neural Network- An USI based Deep Learning Model

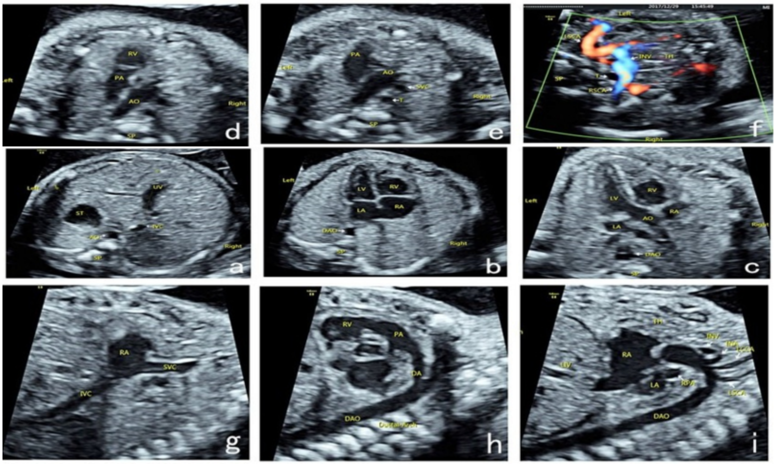

Figure 3. Nine Basic Sections of Fetal Cardiac Ultrasound Images [17]

3 Results And Discussions

Fetal cardiac images are segmented, and it is essential for interpolating the US screening. Some traditional models and region growing [13] are segmented into right and left ventricles. The fetal structures are segmented with the deep learning approaches [14,15]. The fetal cardiac features are distinguished with 14 classes with different views annotated as four Chamber View (4 CHV) and Three vessel Trachea View (3VTV) shown in **Table 1**. Two different images were retrieved from the dataset. Anatomic landmarksfor4CHV and 3VTV include the presence of a complete rib on the chest wall with chambers and valves. Each image is selected individually and segmented manually and then detected with fetal echocardiography, resulting in different numerical segmented output with dice coefficient for various features of fetal cardiac abnormalities shown in **Table 2.**

Table 1. Fetal Structures with distinct Cardiac Views

Fetal Anatomical Structures	**Different Cardiac Views**	**Fetal Anatomical Structures**	**Different Cardiac Views**
Left Ventricle (LV)	4CHV	Superior Vena cava (SVc)	3VTV
Right Ventricle (RV)	4CHV	Trachea (Trc)	3VTV
Left Atrium (LA)	4CHV	Spine(S)	3VTV, 4CHV
Right Atrium (RA)	4CHV	Interventricular Septum (IvS)	4CHV
Descending Aorta (DA)	4CHV	Interatrial Septum (IaS)	4CHV
Pulmonary Artery (PA)	3VTV	Mitral Valve (MV)	4CHV
Aorta (Ar)	3VTV	Tricuspid Valve (TV)	4CHV

Table 2. Numerical Segmentation output

3VTV Technique	PA= 80 ±12	Ar= 79±17	SVc=66±18	TrC= 77±18	S=81±15
4CHV Technique	LV=81±16	RV=82±15	LA=85±10	RA=87±12	DA=81±13
Combined Model	PA= 80 ±12 LV=81±16	Ar= 79±17 RV=82±15	SVc=66±18 LA=85±10	TrC= 77±18 RA=87±12	S=81±15 DA=81±13

Nine features of fetal cardiac functions are described and illustrated as a histogram in **Figure 4.** The fetal cardiac dataset comprises 2127 samples. After preprocessing, 1450 samples are considered for analysis. During segmentation, 1225 samples are accurately segmented and given input to the ANN model, where the segmentation and detection process was carried out in a parallel computing environment. The specific abnormality that includes hole detection is taken for validating the ANN model shown in **Table 3,** and the corresponding proposed model produces high MPI after the detection process [**Figure 5**]

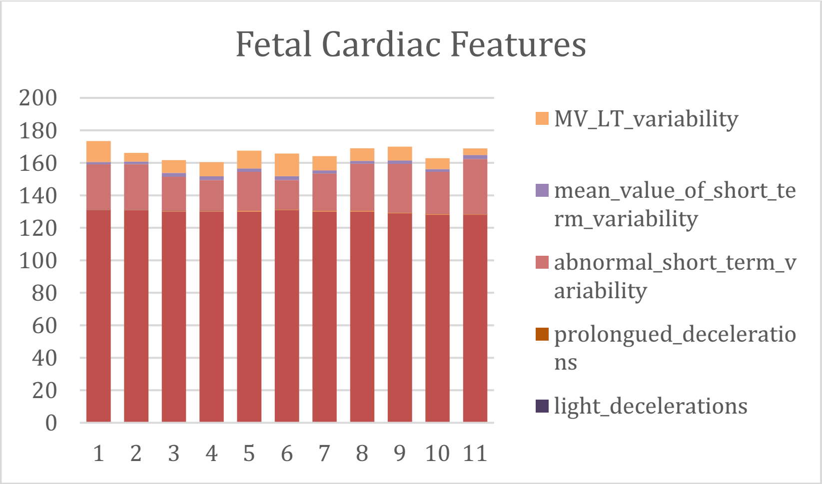

Figure 4. Nine Demographic features of the fetal cardiac images

Table 3. Abnormality Detection during parallel Computing

Specific Abnormality	MPI _ANN with Raw data	MPI _ANN with Segmentation	MPI _ANN with Detection
Hole Detection	85.10	87.57	90.24

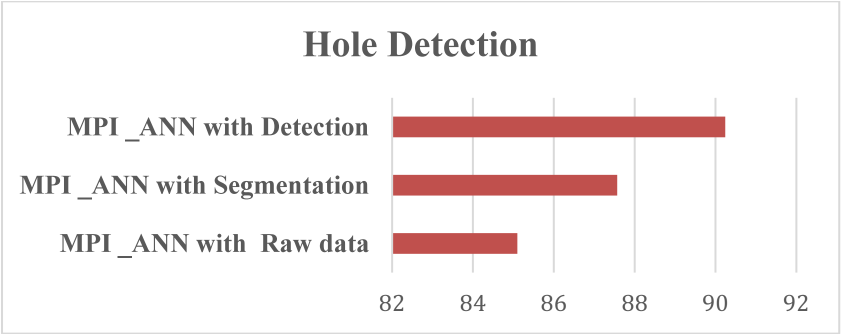

Figure 5. Evaluation metric of the proposed Deep learning Model

4 Conclusion

Fetal cardiac abnormalities detection remains a paradigm among research experts in the medical field. To improve the diagnosis of this cardiac defect, the CCDs need to be progressed to detect cardiac defect with a deep learning model carried out in the proposed model. Based on the USI-based ANN approach, segmentation and detection are done on the ultrasound image data due to the infrequent incidence of CCD in fetal stages. Feature extraction is scaled using different layers in the ANN network with a feed-forward process. The results are evaluated with hole detection performance with MPI metric showing the proposed model produces higher ground truth value. In the future, this deep learning model can be used for the various datasets as the proposed model is carried with a restricted image dataset.

Reference

[1] B. J. Bouma and B. J. M. Mulder, ``Changing landscape of congenital heart disease,'' Circulat. Res., vol. 120, no. 6, pp. 908922, 2017.
[2] Dakkak and T. I. Oliver, ``Ventricular septal defect,'' in StatPearls [Internet]. Treasure Island, FL, USA: StatPearls Publishing, 2018.
[3] C. Mavroudis, J. A. Dearani, and R. H. Anderson, ``Ventricular septal defect,'' in Atlas Adult Congenital Heart Surgery. Springer, 2020, pp. 91115
[4] Z. Jalal, ``Long-term complications after transcatheter atrial septal defect closure: a review of the medical literature,'' Can. J. Cardiol., vol. 32, no. 11,p. 1315, 2016.
[5] P. Garcia-Canadilla, S. Sanchez-Martinez, F. Crispi, and B. Bijnens, ``Machine Learning in Fetal Cardiology: What to Expect,'' Fetal Diagnosis Therapy, vol. 47, no. 5, pp. 363372, vol. 2020, DOI: 10.1159/000505021.
[6] J. Espinoza, ``Fetal MRI and prenatal diagnosis of congenital heart defects,'' Lancet, vol. 393, no. 10181, pp. 15741576, 2019, DOI: 10.1016/S0140-6736(18)32853-8.
[7] V. Rawat, A. Jain, and V. Shrimali, ``Automated techniques for the interpretation of fetal abnormalities: A review,'' Appl. Bionics Biomech., vol. 2018, pp. 111, Jun. 2018, DOI: 10.1155/2018/6452050.
[8] L. Allan, J. Dangel, V. Fesslova, J. Marek, M. Mellander, I. Oberhänsli, R. Oberhoffer, G. Sharland, J. Simpson, and S.-E. Sonesson, ``Recommendations for the practice of fetal cardiology in europe,'' Cardiol. Young, vol. 14, no. 1, pp. 109114, Feb. 2004, doi: 10.1017/s1047951104001234
[9] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun ACM 2017;60(6):84–90.
[10] Wang G. A perspective on deep imaging. IEEE Access 2016; 4:8914–24.

[11] Rittenhouse KJ, Vwalika B, Keil A, Winston J, Stoner M, Kapasa M, et al. Improving preterm newborn identification in low-resource settings with machine learning. PLoS One 2019, Feb; 27:e0198919. 44 Hamilton EF, Dyachenko.

[12] A, Ciampi A, Maurel K, Warrick PA, Garite TJ. Estimating risk of severe neonatal morbidity in preterm births under 32 weeks of gestation. J Matern Fetal Neonatal Med. 2020 Jan; 33(1): 73–80.

[13] Punya Prabha, V., Sriraam, N., and Suresh, S., \Hybrid segmentation approach to segment fetal cardiac chambers of ultrasound images," in [International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering], 331{334 (2019).

[14] Xu, L., Liu, M., Zhang, J., and He, Y., \Convolutional-neural-network-based approach for segmentation of apical four-chamber view from fetal echocardiography," IEEE Access 8, 80437{80446 (2020).

[15] Yang, T., Han, J., Zhu, H., Li, T., Liu, X., Gu, X., Liu, X., An, S., Zhang, Y., Zhang, Y., and Shen D, Wu G, Suk HI. Deep learning in medical image analysis. Annu Rev Biomed Eng 2017;19(1):221–48.