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ARTIFICIAL INTELLIGENCE BASED REAL-TIME RECOGNITION OF CARDIAC OBJECTS IN PRENATAL ECHOCARDIOGRAPHY

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Abstract

The most crucial component of prenatal diagnosis is the assessment of the unborn cardiovascular structure and anatomy using the ultrasound procedures. It is inevitable that the conventional approaches pose problems owing to the abundance of speckles in ultrasound videos, the diminutive size of fetal cardiac structures, and its unfixed fetal postures. So, a deep learning model was generated to fully automate the analysis of 2-dimensional cross-sectional images from fetal echocardiography in order to address these problems. This paper provides a real-time fetal cardiac substructure detection using electrocardiography video with the U-Y net framework. It predicts cardiac substructure objects, boxes, and class probabilities. Fetal echocardiography footages were trained using the newly developed U-Y Net architecture based on YOLOV7 neural network and then improved to function optimally in order to obtain consistent results. In order to assist ultrasound professionals to identify the fetal heart standard segment in echocardiography, a powerful machine-learning recognition model is designed by integrating ultrasound images with AI technology. The samples of the fetal apical four-chamber heart, three-vessel catheter, three-vessel trachea, right ventricular outflow tract, and left ventricular outflow tract has been collected at 20–24 weeks during pregnancy from a various hospital. The results of the experiment indicate that this technique can successfully distinguish between the anatomical components of various fetal heart sections and evaluate the standard sections in accordance with these anatomical components. This emphasizes a strong foundation for diagnosing congenital heart disease of fetus using by ultrasound imaging procedures.

Keywords: *Left Atrium (LA), Right Atrium (RA), Left Ventricle (LV), Right Ventricle (RV), Tricuspid Valve (TV), Pulmonary Valve (PV), Mitral Valve (MV), Aortic Valve (AV), Aorta (Ao), You Only Look Once (YOLO), Deep Learning (DL), Ventricular Septal Defect (VSD), Atrial Septal Defect (ASD).*

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1. Introduction

Automated interpretation of echocardiography videos [1] has the potential to transform medical procedures in a number of ways which includes making it possible for the non-specialists to assess the cardiovascular health in general medical practice and agrarian environments [2]. Early prenatal diagnosis of the majority of congenital heart problems is possible using the ultrasound diagnostic procedures performed in the utero [3]. The echo cardiography perceptions may differs due to several factors such as the phase of pregnancy , variations in utero as the gestational age increases [4]. But due to its noninvasive quality , affordability, and portability, fetal echocardiography is a crucial component of prenatal cardiac health screening for all pregnancies globally. As a result, interpretation of fetal echocardiography videos is necessary and dependent in monitoring the physiological evaluation of a growing fetus [5].

In order to detect the entire cardiac substructure for any abnormalities through echocardiography, the complete cardiac structure should have to be distinguished in terms of regular anatomical structures. The four main normal anatomical structures present in the heart are the four main chambers such as the left atrium (LA), right atrium (RA), left ventricle (LV), and right ventricle (RV) , the four valves such as the tricuspid (TV), pulmonary (PV), mitral (MV), and aortic (AV), and aorta (Ao), which carries oxygen-rich blood throughout the body [2,3,6].

Manually assessment need proper and exact cardiac substructure analysis from echocardiography video requires specialized training based on theoretical and hands-on experience. But there are some limitations to the conventional practice are that Interpersonal variations. Interpersonal variation means that the analysis rely on the abilities of the examining clinician and the patient's health state which is one of the biggest restrictions associated with the ultrasound videos [7].

Numerous speckles in echocardiography videos, the small dimensions of the prenatal heart, the not fixed fetal postures due to different gestation period, and challenges in distinctions produced due to the resemblance of cardiac chambers make it extremely challenging to analyze the fetal cardiac substructures [8]. In order to alleviate these issues, the computer-aided approach which can assists medical practitioners in automatically recognizing fetal cardiac substructures has garnered a lot of interest recently [9,10]. Such techniques can aid medical professionals in automatically identifying fetal cardiac structures and may play a significant role in the early detection of congenital heart disorders of fetus.

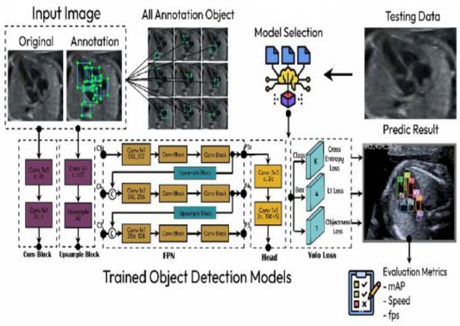

Figure 1: General Process Involved in Detecting Ardiac Substructures from Fetal Echocardiocardiography Videos

Due to its remarkable capability to learn invariant features, deep learning (DL) approach has become a contemporary approach in ultrasound imaging for the interpretation of fetal echocardiography [11-17]. The devices used in the contemporary approaches simulate cognitive functions such as learning, applying, and solving intricate problems. The Convolutional neural networks (CNNs) possess significant ability to train features robust from medical images. In the work proposed by Zhang et al. [2], a DL model was implemented to completely automate the processing of echocardiography covering all the functionalities of diagnosis such as diagnosis of disease, segmentation of images, and quantification of structure and function. Real-time fetal cardiac object detection based on echocardiography video would significantly speed up processing and lead to accurate diagnoses [18–20].

A Deep Learning model has been described for real-time recognition in freehand ultrasound imaging technique was devised by Baumgartner introducing the approach named SonoNet [21]. This approach provided a instantaneous object recognition based on You Only Look Once (YOLO) [20]. A YOLO network totally achieves end-to-end optimization of detection performance by directly predicting the location and class probability of objects.

The goal of this work was to develop an efficient model that will lessen the significance of detrimental effects created by certain components on ultrasound technicians. And it also boosts the accuracy of the standard fetal cardiovascular ultrasound image recognition process which helps medical practitioners in improving the accuracy of fetal cardiac prenatal assessment.

2. Related Work

Computation has gained a lot of attention in healthcare studies as a result of the advancement and use of artificial intelligence (AI). In 2008, the researchers Liu et al. [22], demonstrated that AI is more effective than manual search while screening optimal cross-sections in three-dimensional echocardiography. Then in the later work, Yi and Babyn [23] developed a frame work by modifying the pertinent parameters which leads to the increase in the capability of AI for identifying the computer Tomography (CT) images. A navigation visualization system for standard transesophageal echocardiography was developed in 2015 by Yuhuan et al. [24] .This system realized the real-time localization of the transesophageal probe. This effectively supported medical professionals in improving their comprehension about the three-dimensional structure of the cardiovascular system.

A deep convolution generation countermeasure network (DCGAN) was deployed by Madani et al. [25] in 2018 to synthesize of chest X-rays. In that work, they employed two GANs to produce normal and pathological chest X-ray images, and also assessed the efficiency of the classification performance with that of the radiologists' recommendations. In the later work performed in the same year by Zhang et al. [26], the accuracy of tissue images was found to be more improved with the implementation of the enhanced GAN.

Due to the advancements in the technology, AI has been used for performing prenatal ultrasound assessment of fetus face and brain developed by Chen [27]. This framework precisely determines the size of the fetal lateral ventricle in ultrasound images. Xie et al. [28] devised a framework which encompasses the subtasks such as image recognition, localization, and segmentation of fetal skull images.

In a later work, Lei et al.'s [29] successfully attained a excellent performance measure in recognizing fetal facial substructures. The utilization of deep learning (DL) and machine learning (ML) in the fetal cardiac health screening remains in its early stages. According to the research conducted by Wang et al. [26] a framework using Deep Learning technique which makes use of echocardiography information such as ventricular septal defect (VSD), and atrial septal defect (ASD) to produce the diagnostic impact with an accuracy rate of more than 90%.

Xu et al. [16] conducted a large number of experiments on the four-chamber view dataset, which showed that DW-Net had a good segmentation effect specific on the four-chamber view.

It has been challenging for conventional manual classification techniques to fulfill the demands of high-performance object detection process. So, the fully automated DL technique has captivated individuals' concern.

The DL network has several hidden layers and many perceptrons for describing the features of the image in a more in-depth and advanced level. It optimizes the traditional feature extraction approach [31] and eliminates the problems that arise during the feature extraction process. Deep belief networks (DBN), convolution neural networks (CNN) [32], recurrent neural networks (RNN), and generalized adversary networks (GAN) are the four primary types of DL used in image recognition. In the previous researches, it has been demonstrated about that CNN is capable of processing diverse image processing tasks in an efficient and effective way [33, 34]. In this work, a CNN feature called YOLOV7 is chosen to create an experimental model. This paper suggests a YOLOV7 deep convolution neural network-based fetal cardiac standard recognition model (U-Y-net).

3. Material and Method

The work incorporates the three primary phases: fetal cardiac image acquisition and annotation, fetal cardiac substructure detection using YOLOv7, and evaluation and validation.

Fetal Cardiac Image Acquisition and Annotation

For the experiment on real-time fetal cardiac anatomical structures detection in echo cardiography videos, the dataset has been acquired from patients who are undergoing normal prenatal procedures. Experienced professionals were used for acknowledging all echo cardiography videos of fetuses between 18 and 24 weeks of gestational age. The hardware requirements employed for the imaging process of echo cardiography was GE Voluson E6 equipment.

The smaller dimensions of the fetal heart and issues in distinguishing features are considered to be a major hurdle in detecting fetal cardiac substructure objects [9–11]. The clinical report for each echocardiography footages was examined to determine the fetal heart normal anatomical function, and also the experts were employed for performing the task of annotating the chosen fetal echo cardiography video for the learning phase. Then the images are archived in Digital Imaging and Communication in Medicine (DICOM) format. The DICOM images are represented as a gray scale bitmaps. Fig. 2 shows some examples of annotated fetal cardiac structures using any Open Annotation software Tools.

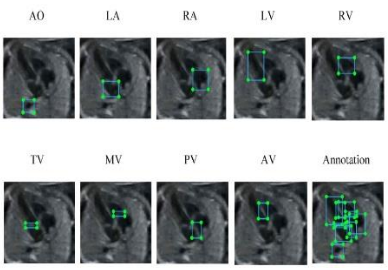

Figure 2: Annotation of Fetal Cardiac Structures

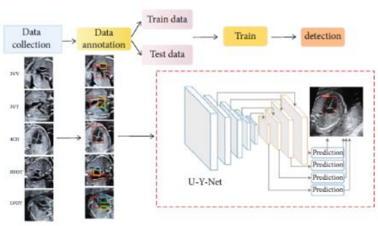

Figure 3: Workflow of Model Construction and Verification

Proposed Fetal cardiac substructure Detection using U-Y Net using YOLOv7 .

The proposed architecture is a U-Y Net based YOLOv7 frame work. The real-time object detection efficiency is significantly increased by YOLOv7 without rising the inference costs. YOLOv7 outperforms other well-known object detector algorithms by reducing the parameters as well as the computation task. This leads to robustness and improvised detection precision. The YOLOv7 [35] architecture comprises of the Input layer, Backbone named E-ELAN means Extended Efficient Layer Aggregation Network, Feature Pyramid Network - FPN and loss functions.

E-ELAN provides an efficient learning process by managing the shortest and longest gradient paths in YOLO architecture. The model scaling is done by concatenating layers together. The YOLOv7 framework is used for the first time in this paper to examine real-time fetal cardiac substructure detection in all the standard planes of echocardiography.

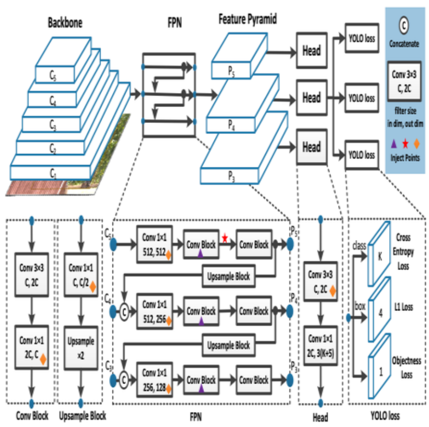

Figure 4: YOLOv7 Architecture

Evaluation

Based on the mean average precision (mAP) value, our model was validated. The confusion matrix (CM), the IoU, the recall (R), and the precision are the metrics used to calculate the average precision (AP). The parameter "mean average precision" (mAP) refers to the average precision calculated across all classes. The frames per second (FPS) metric is another parameter used to validate our object detection model for analyzing the echocardiography videos. Based on the mAP value, the performances of YOLOv5n, YOLOv5s, YOLOv6n, YOLOv6s, YOLOv7, and YOLOv7-tiny were evaluated.

The proposed model detected nine cardiac structures in echocardiography videos. The proposed YOLOv7 model successfully identified the nine fetal cardiac objects' boundaries. The rate at which each and every object detected provides satisfiable results by achieving a maximum object score of almost 91% and a minimum score of 30%.

Table 1: Performance of Various Yolo Models

Object	mAP Performance (in Percentage)		
	YOLOv5	YOLOv6	YOLOv7
LA	89.50	67.56	90.40
RA	86.20	52.23	92.20
LV	88.30	43.21	94.80
RV	75.50	77.81	88.30
AO	88.60	83.51	87.40
TV	72.00	71.12	66.80
MV	66.70	66.45	69.20
PV	63.70	80.01	71.20
AV	76.00	86.32	78.40
Avg.mAP	**78.50**	**67.35**	**82.10**

Table 2: Model Evaluation Comparison

MODEL	SIZE	FPS	mAP
YOLOv5	640	25	1.30
YOLOv6	640	18	1.10
YOLOv7	640	17	0.80

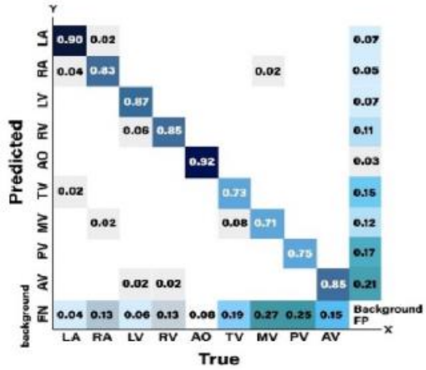

Figure 5: Confusion Matrix of YOLOv5s Architecture

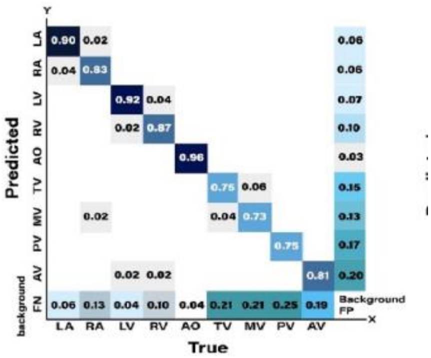

Figure 6: Confusion Matrix of YOLOv6s Architecture

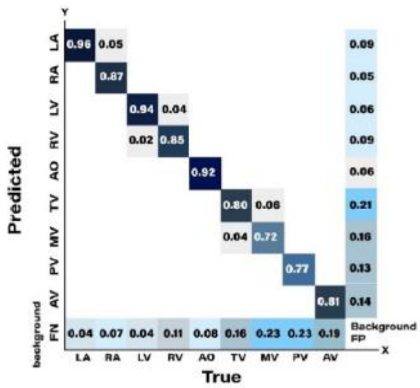

Figure 7: Confusion Matrix of YOLOv7 Architecture

The proposed YOLOv7 based U-Y-net is more sensitive and accurate than that of the medical practitioner's detection precision. Therefore, YOLOv7 based U-Y-net's overall object recognition accuracy and sensitivity is superior compared to that of the primary intermediate level. This paper demonstrates that U-Y-net can successfully recognize a number of significant cardiac structures of the echocardiography images and has a positive impact on the classification of nine cardiac structures such as LA, RA, RV, LV, TV, MV, PV, AV and AO in echocardiography assessments. This work surpassed the other YOLO architectures used deep learning. This study uses the YOLOV7 approach. Deep learning is constrained by the quantity of data, model effectiveness, training time, usage of resources, and the imbalances in allocation of resources to the system. Future research will concentrate on how to better improve the recognition efficiency and also aid in assisting medical practitioners to acquire in depth knowledge about congenital heart defects more knowledge and also in supporting them during diagnosis.

4. Conclusion

In this paper, an automated echocardiography analysis enables health care easier to access. . The nine fetal cardiac anatomical structures RA, LA, RV, LV, TV, PM, MV, AV, and AO were precisely identified in real-time using the YOLOv7 model. Even with an inadequate training set of echocardiography videos, the proposed YOLOv7 based U-Y Net model demonstrated promising outcomes for fetal cardiac recognition. The outcomes of the validation results show that the model can be used to a diverse fetal cardiac anatomical function. Since the first phase in congenital heart disease research is the identification of nine significant fetal cardiac sections. The DL model benefit health care providers in monitoring the cardiac health of fetus by eliminating the negative consequences involved in the conventional fetal cardiac health screening system.

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