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Advances in Deep Learning for Fetal Cardiac Anomaly Detection: A Review

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Abstract

This paper presents an extensive review of cardiac anomaly detection and classification in fetuses from a deep learning perspective. Anomaly detection is important because fetuses are affected by various cardiac anomalies, leading to mortality or severe complications in the later stages. Hence, early detection of anomalies is essential for further treatment. Our paper mainly discusses the application of deep learning techniques and the promising results obtained for anomaly detection in 1-Dimensional, 2-Dimensional and 3-Dimensional data. These studies suggest that deep learning models can be effective in detecting fetal state conditions and the specific structure of the fetal heart. Some promising results include the one-dimensional convolutional Neural Network model, which achieved 97.46% accuracy in detecting the fetal state condition, and the recurrence plot Convolutional Neural Network, which achieved 98.6% accuracy in detecting fetal hypoxia. In 2-Dimensional data, an ensemble of neural networks achieves an Area under Curve of 0.99 for detecting cardiac substructures, and the Mask Recurrent Convolutional Neural Network provides astonishing results in multiclass detection. The cropping segmentation calibration method yielded the best results for detecting and partitioning the ventricular septum in the 3D ultrasound data. However, each method has its own merits and limitations, and future work can be conducted to improve the performance of these methods, such as using larger datasets or developing more advanced training strategies

Keywords: Anomaly, Fetus, Cardiac, Deep Learning, Cardiotocography, Ultrasound, Echocardiography

1. Introduction

Cardiac anomalies in fetuses are a major concern in prenatal care because of their association with high mortality rates and severe postnatal complications. The early and accurate detection of these anomalies is crucial for timely medical intervention, which can significantly improve health outcomes. Despite advancements in medical imaging and diagnostic techniques, there remains a critical need for more reliable, efficient, and scalable methods to detect and classify fetal cardiac anomalies. Anomaly detection has a vast range of applications in the detection of intrusion, Fraud, Medical, and Public Health anomalies, Industrial Damage, Text data, Image Processing, and Sensor Networks [1]. Because the fetus is affected by various anomalies, especially congenital heart defects, it is necessary to rectify these anomalies in the womb. Congenital Heart Disease (CHD) is a frequent ailment with a prevalence of 8 out of 1000 births. The majority of baby and childhood mortality due to congenital abnormalities is thought to be due to heart defects. A poor prognosis is also associated with a diagnosis of congenital cardiac disease before birth. Intrauterine congenital abnormalities are thought to be caused by heart defects. A poor prognosis is also associated with a diagnosis of congenital cardiac disease before birth. The intrauterine survival longevity is low, ranging from 15-40 percent. Extracardiac defects and chromosomal disorders play a role in poor prognoses. Other deformities that affect fetal death occur in 20–30 percent of cases, newborn death in 40-60 percent of cases, and extended complications. In this short-axis image, the right ventricular outflow tract wraps on every side of the aorta, as it exits the heart. The percentage of fetuses with congenital cardiac disease is 25–45%, and 15–50 percent have abnormalities [2]. As fetuses are affected by various congenital diseases, numerous anomalies are detected during the gestational period of 11-13 weeks, between the first and second trimesters, which helps in further treatment decisions[3]. The Various fetal cardiac anomalies include truncus arteriosus, ventricular septal defect, Tetralogy of Fallot, Av septal defect, double outlet RV [4], single ventricle, hypoplastic left heart syndrome, Ebstein anomaly, atrial septal defect, aortic coarctation or hypoplasia, pulmonary stenosis, and arrhythmia [5]. It is essential to understand the cardiac cycle before assessing fetal cardiac function. The main function of the heart is to release blood into all the organs. The main factor is the diastolic stage, in which blood moves from the auricle to the ventricles. The period of systole is the blood movement from the ventricles to the aorta and pulmonary arteries. The five cardiac cycle periods were isovolumetric relaxation, early diastole, atrial contraction, isovolumetric contraction, and ejection. The parameters that determine changes in the function and shape of the heart are myocardial contractility, fiber orientation, volume and pressure loading conditions, and maturational changes [6]. Cardiac anomaly detection is a complex task performed between 18 and 22 weeks using fetal cardiac ultrasound. Fetal echocardiography is performed for high-risk fetal, maternal, and familial factors. Fetal factors include increased nuchal translucency, hydrops, polyhydramnios, and extracardiac anomalies. Maternal factors include congenital heart defects, metabolic disorders, teratogen exposure to autoantibodies, and folic acid deficiency. Familial factors include fathers or siblings with congenital heart defects and Mendelian syndromes [7]. Deep learning, an evolution of machine learning at present, has been used to predict and examine unstructured datasets, and hence provides good care for patients [8]. All detection methods suffer from complex problems during the detection process. Newly emerging deep learning-enabled deep anomaly detection incorporates three prototypes: End-to-end Anomaly Score Learning, Feature Representations of Normality, and Deep Learning for Feature Extraction Learning [9]. The multilevel learning and regularization implemented in the deep neural network to raise its standard and firmness is beneficial for imaging problems such as registration and classification [10]. Deep-learning-based anomaly detection has expanded widely in all applications, particularly in the medical field. Some challenges in the detection of anomalies include the availability of labelled data and the difficulty in identifying noise close to anomalies [11]. Anomalies can be classified into three types: contextual, point, and collective. Owing to the enormous amount of available medical data, the prediction of outliers is a demanding task [12]. The novelty of this study lies in the comprehensive comparison of these deep learning methods across different data dimensions, highlighting their specific advantages and limitations. It categorizes the use of various types of medical data, such as 1D (Dimensional) fetal heart signals, 2D ultrasound images, and 3D ultrasound videos. Performance metrics, such as accuracy and Area Under Curve (AUC) values, are discussed, demonstrating the potential of these models. In addition, we provide insights into future research directions, such as leveraging larger datasets and developing more sophisticated training strategies, to further enhance the performance of these models.Overall, it synthesizes diverse studies, highlights the model performance, and suggests future advancements.

1.1 Modalities for anomaly detection

The original source of information for scrutiny applications is video. Because there are many video materials, they have few or no interpretations of supervised learning. Unsupervised models for detecting anomalies in videos are based on generative, spatiotemporal predictive, and reconstruction models [13]. The identification and depiction of anomalies can be performed using fetal cardiac ultrasound in four-chamber and outflow tract views. Anomalies can also be detected using a transvaginal scan even at 12-13 weeks. Although there are more limitations due to the size and heart rate of fetuses, functional fetal echocardiography acts as an optimistic tool and helps to detect fetal conditions, including maternal diabetes, twin-to-twin transfusion syndrome, congenital diaphragmatic hernia, and intrauterine growth restriction [14]. Vascular and valvular lesions were evaluated by Doppler imaging. Fetal echocardiography is used to evaluate extracardiac anomalies, especially in high-risk pregnancies. Three-dimensional and four-dimensional imaging enable the reformation of many complex planes from an individual transverse acquisition and cine looping of images in different planes, which helps in the estimation of cardiac movements and functions [15]. 4D ultrasonography has become the first option for cardiac assessment, as more advances have been made to enhance the volume of images and develop spatial and temporal resolution, with Doppler tissue and B-flow imaging being a segment intersecting the 4D mode. The small 4D probes contained in endoscopic ultrasound can be used to guide fetal cardiovascular intervention transoesophageally or intracardially. In the long run, Magnetic Resonance Imaging (MRI) at a high speed is the second option. When details are collected in this manner and multimodal and multidimensional pictures and signals are fully exploited for cardiac modeling, fetal heart disorders are upgraded, including a fundamental understanding of in utero cardio physiology [16]. A novel method FINE(Fetal Intelligent Navigation Echocardiography) is suggested for imaging of standard fetal echocardiography perspective from volume datasets acquired with intelligent navigation technology and spatiotemporal image correlation [17]. In recent years, fetal cardiac magnetic resonance imaging (FCMR) has emerged as a valuable imaging modality for evaluating fetal cardiovascular structures. Cardiovascular morphology is assessed using FCMR and helps investigate the development of cardiovascular structures in relation to gestational age (GA) in pregnant women [18].

2. Method:

2.1 Publications by year

The papers used for this review included publications published from 2009 to 2025. The number of publications gradually increased from 2002 to 2021, peaking at 11 in 2021. The years with the highest number of publications were 2017, 2018, 2020, and 2021. Overall, the publications used in this review covered 16 years and showcased advancements in the field during that period. Figure 1 illustrates these publications over time.

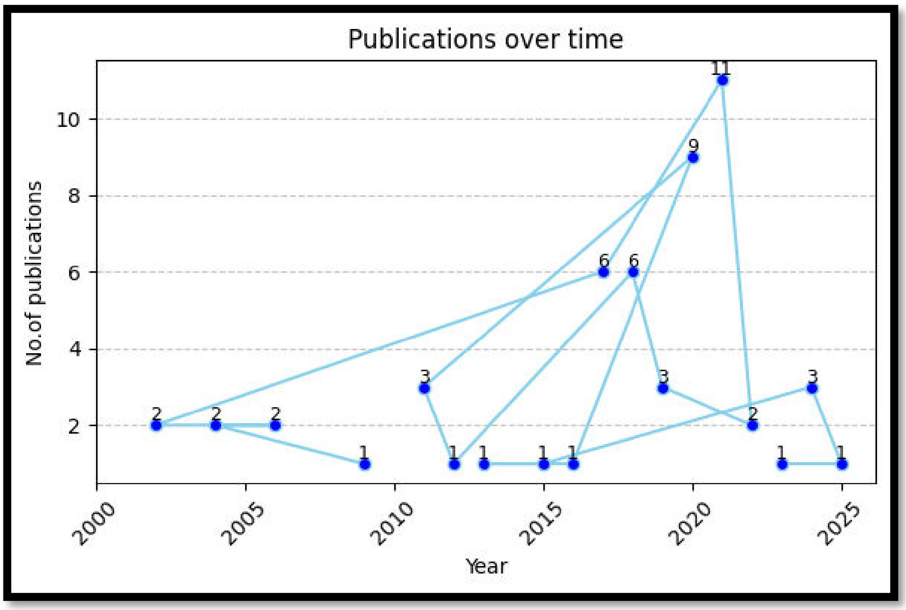

Fig: 1 Illustration of publications over time

2.2 Contribution with respect to the data

Of the 58 publications, 19 presented 1D data, 11 showed 2D data, and seven included 3D data. The use of different types of medical data for detecting fetal heart anomalies can be categorized as follows: 1D data use fetal heart signals that primarily employ CTG data. 2D data mainly utilize ultrasound and echocardiography images. The 3D data predominantly consisted of the ultrasound videos.

Figure 2 shows the piechart representing the number of publications in 1D, 2D, and 3D data.

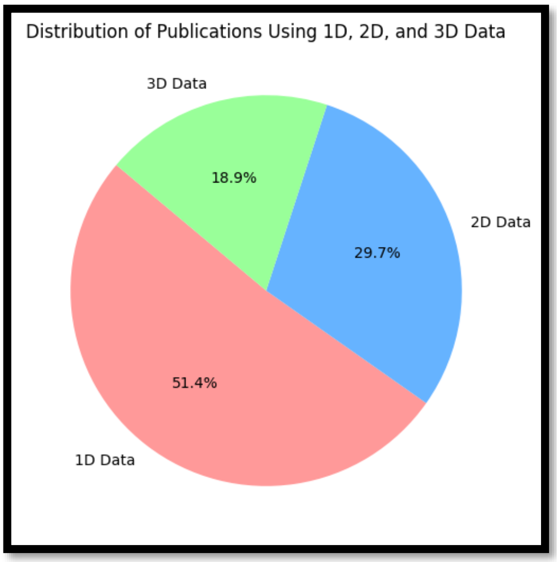

Fig:2 Representation of Pie chart

3. Detection of fetal cardiac anomalies using deep learning

Deep learning models enhance diagnostic accuracy and reliability, reduce human error, and efficiently process large volumes of data. They enable detailed analysis of complex data and improve the detection of fetal heart anomalies. These models provide a standardized objective analysis, detect subtle anomalies, seamlessly integrate into clinical workflows, and offer reliable diagnostic support in areas with limited medical professionals. In this study, we conducted a survey on the application of deep learning techniques in fetal anomaly detection. In this study, 1D, 2D, and 3D datasets were used. Here, we discuss the specific techniques and objectives for each set of specified data. The results obtained by implementing various techniques are also provided in detail with respect to the different performance metrics. In addition, we have described in detail the merits of these methods, as well as their limitations and future work that can be performed using these methods. The sections are arranged as follows section 3.1 give us the application in 1D data, Section 3.2 describes the application in 2D data, and Section 3.3 gives in detail the applications in 3D data.

3.1 One-Dimensional data

To detect cardiac anomalies in 1D data using deep learning, the cardiotocography dataset from the ML repository is mostly used. The Detection of fetal state assessment in 2126 samples of CTG using the present 1-D CNN is more productive than the previous 1-D Convolutional Neural Network (CNN) and executed classifiers [19]. The DW-Net is implemented for the automatic detection of A, E, and V waves on PW Doppler traces to precisely predict and partition DAO (Descending Aorta), LA (Left Atrium), RV (Right Ventricle), RA (Right Atrium), LV (Left Ventricle), EP (electrophysiology), and thorax in the A4C (Apical 4 Chamber) view. It also overcomes problems such as artifacts, the absence of boundaries, noise, distinctions in the angles of screening, and the likeness of anatomical structures [20]. The sub-adaptive neuro-fuzzy inference system with a multi-layer architecture is used for predicting fetal state classes and also improves the productivity and functionality of achieving fetal echocardiography by diminishing the time required to obtain standard views [21]. A Recurrence Plot with CNN is used to detect fetal hypoxia and achieves superior classification accomplishment in detecting fetal hypoxia using Fetal Heart Rate (FHR) signals [22]. The extreme gradient boosting algorithm-based model proposes the automatic detection of fetal health status and has the potential to distinguish conditions more effectively [23]. Another approach to artificial intelligence is to differentiate the existence or absence of different class patterns of morphology, which is an extremely specific and consistent diagnosis for fetal assessment [24]. The deep Gaussian processes used for the categorization of FHR consistently segregate abnormal from normal ones accurately in CTG data [25]. The Long Short-Term Memory (LSTM) network was used for fetal distress detection and feature extraction. It is suitable for feature extraction and feasible for detecting fetal distress [26]. Modular neural network models are used for the detection and classification of fetal states, and can function as classifiers for the present CTG fetal state categorization [27]. A feed-forward neural network and Extreme Learning Machine (ELM) were used for the Categorization and Comparison of CTG Signals, and different types of ELM can be used in future work [28]. The CNN model is used for QRS complex detection, and this method attains good QRS complex detection evaluation from raw NI-FECG (non-invasive fetal electrocardiogram) signals other than canceling MECG (Maternal Electrocardiogram signals (MECG) [29]. The developed deep learning method helps to detect fetal hypoxia and increases its detection capability [30]. A deep CNN with a transfer learning approach is a useful tool for detecting and categorizing FHR signals as abnormal or normal [31]. Model-based Deep Forest is used to solve normal and suspicious class problems in antepartum CTG classification, which is effective and attainable and has the desired execution prospect in antenatal fetal health state evaluation [32]. A novel, consistent, and robust diagnostic model combining ANN, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) was used to predict fetal hypoxia [33]. The SONO architecture, a CNN-based method, detects cardiac abnormalities in fetal ultrasound videos with high accuracy using a barcode-like timeline for visualization [34]. In this study, they employed Mask-RCNN with ResNet50 to detect and segment septal defects in fetal heart ultrasonography, which achieved high accuracy in multiclass detection of cardiac chambers and reliable defect identification. [35]. The MRHAM-YOLOv4-Slim model, which integrates a multistage residual hybrid attention module (MRHAM), enhances feature learning and accurately detects fetal four-chamber views in ultrasound images, achieving a high precision and F1 score. [36]. This study introduces a CNN-based method for real-time detection and localization of 13 fetal standard views in 2D ultrasound using weak supervision to annotate and retrieve frames with high accuracy [37]. The fetal CTG signal sample is shown in Figure 3 [38].

Table 1. Overview of the application of deep neural networks in 1D data for cardiac anomaly detection in the fetus

Author	Methodology	objective	Datasets	Results	Merits	Limitation/Future work
[19]	1-D CNN	Detection of fetal state condition	2126 CTG data	Accuracy – 97.46%	Effective than previous 1-D CNN	To implement real-time stream processing for object detection
[20]	DW-Net	Automatic detection of E, V, and A waves on PW Doppler traces	Traces of LV inflow–outflow PW Doppler from 5 healthy fetuses	Dice Similarity Coefficient - 0.827 Pixel Accuracy - 0.933 AUC - 0.990	overcomes problems including artifacts, Absence of boundaries, noise, distinctions in angles of screening, and likeness of anatomical structures	To resolve segmentation problems in views of fetal cardiac ultrasound, such as the left ventricular outflow tract view and three-vessel view.
[21]	The multi-layer architecture of a sub-adaptive neuro-fuzzy inference system	For predicting various fetal state defects	CTG data	90% in obtaining the diagnostic plane left ventricular outflow tract 98% in obtaining the angles line	Improves proficiency Decreases the time in obtaining standard cardiac views	Inefficient in detecting the other congenital anomalies
[22]	Recurrence Plot with Convolutional Neural Network	To detect fetal hypoxia	FHR signals	Accuracy - 98.69%, Sensitivity - 99.29%, Specificity - 98.10%, The area under the curve - is 98.70%.	Achieves the best performance in predicting fetal hypoxia using FHR signals	Combinationof the FHR signal with other biomedical signals to develop accuracy

[23]	Decision boundary-based Anomaly detection model using improved AnoGAN	To detect and classify the data	MIT-BIH arrhythmia ECG data	AUC - 0.9475 F-measure - 0.9143	Best performance in Arrhythmia detection	The limitation is the requirement of labeled data though they perform well.
[24]	an alternative approach to artificial intelligence	To differentiate and categorize the presence or absence of different class patterns	CTG database	Accuracy - 88.02% Recall - 84.30% Precision - 85.01%, F1-score – 85.08%	Highly accurate and consistent for assessment.	To use dropout technique as an adaptive regularization for adaptive ensemble learning.
[25]	supervised and unsupervised learning by deep Gaussian processes	categorization of FHR tracings.	CTG recordings	Sens- 82% spec-91% Geometric mean- 86%	To differentiate the abnormal FHR recordings from the normal ones accurately	Not mentioned
[26]	Long Short-Term Memory network	Fetus distress detection and feature extraction	Fetal heart rate signals	Accuracy -83% Specificity-82%	It has the supremacy and proficiency of DL in feature extraction and fetal distress detection	Extremely small and uneven data distribution.
[27]	Modular neural network (MNN) models	Detection and classification of the fetal state	2126 fetal CTG signal recordings data	The suspect classification rate is between 90.65 - 98.46%. The normal classification rate is more than 99%	The MNN-based model with an error backpropagation algorithm can be used as an outstanding classifier for the given CTG fetal state categorization task.	Not mentioned
[28]	Feedforward neural network and Extreme	Classification and Comparison of CTG Signals	2126 records in UCI Machine Learning	Accuracy of ANN – 91.84% ELM - 93.42%	The training time is faster	various types of ELM can be utilized

	Learning Machine		Repository			
[29]	convolutional neural network model.	fetal QRS complex detection	raw NI-FECG signals	High precision - 75.33% Recall - 80.54% F-score-77.85%	The proposed method attains acceptable fetal QRS complex detection performance from the raw NI-FECG signals short of cancelling MECG signals.	Not mentioned
[30]	improved deep learning method	To detect hypoxia	CTG database	Accuracy-81%	Increases capability in detection	Not mentioned
[31]	Deep CNN with the transfer learning approach	To detect and classify FHR as normal and abnormal signals.	open CTU-UHB database	Accuracy – 94.1%	DCNN is found as an effective tool to detect fetal hypoxia.	To use CNN-based classifier on larger databases.
[32]	Model based on Deep Forest	To solve the crossover between normal and suspicious class problems in antepartum CTG classification	CTG data set	Accuracy - 92.64 % Average F1 value - 92.01 % Area Under the Curve - 0.990	The proposed DF model is effectual and attainable and has a good approach	To collect antepartum pathologic cases to achieve various classifications.
[33]	Combination of ANN, SVM, and KNN	predicting fetal hypoxia	CTU-UHB Intrapartum CTG database	Accuracy - 94.75% Sensitivity - 74.29%, Specificity-99.55%.	It is a new, continuous, and fast diagnostic model certified for predicting fetal hypoxia.	To validateon greater datasets
[34]	Dubbed Domain Adversarial Training Of Neural Network For	For data classification	CTG data set	Accuracy-71.25% F1 Score-76.08% AUC- 77.05%	The DANNMCTG algorithm demonstrates enhanced capability in extracting	To leverage pseudo-labels for enhancing the generalization of domain adaptation algorithms

	Multicenter CTG (DANNMCTG)				domain-invariant features. It also exhibits superior performance	
[35]	A single-stage fetal cardiac ultrasound standard plane detection model (FCUM) based on multitask learning and a hybrid attention mechanism	To improve detection efficiency and reduce misdiagnosis and omission.	Fetal ultrasound Image dataset	**Four Chamber Section** Precision- 99% Recall- 99% F1-Score- 99% **Left Ventricular Section** Precision- 99% Recall- 97% F1-Score- 98% **Right Ventricular Section** Precision- 97% Recall- 97% F1-Score- 97% mAP@0.5:0.95 - 73.6	This work can effectively relieve clinical sonographers' work pressure and reduce the dependence on physicians' experience for prenatal fetal heart screening	To focus on the engineering implementation and other medical image detection.
[36]	A Deep Learning-based Fetal Heart Ultrasound Standard Planes Recognition Network (FHUSP-NET)	To have rapid and accurate prediction of fetal heart growth	3360 ultrasound images of five Fetal Heart Ultrasound Standard Planes	Precision-95.8% Recall-93.1% Accuracy-96.4%	This method helps to improve ultrasonographers' quality control of the fetal heart ultrasound standard plane and aids in the identification of fetal heart structures in a less experienced group of physicians.	To achieve the contour segmentation of the fetal heart structure To understand the growth of the fetal heart.
[37]	Cloud-GAN model	To improve the low-dimensional representation and reconstruction accuracy for superior performance on high-dimensional datasets with	CTG data FHD data FTR data	Precision – 77% Recall – 77% F1-score – 77% Precision – 53% Recall – 53% F1-score -53% Precision – 74 % Recall – 72 % F1-score -73 %	Cloud-GAN shows limited advantages in low-dimensional datasets, as mean and variance effectively preserve and reconstruct such data after dimensionality reduction.	To involve extensive evaluation of our method on higher-dimensional, image, and video datasets,

		limited training samples.				

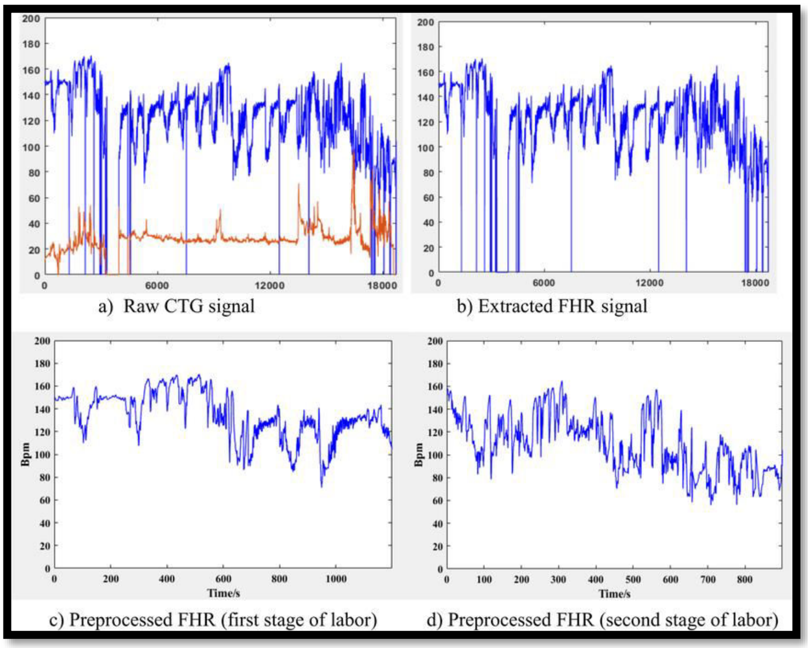

Fig:3 Representation of Fetal CTG Signal

3.2 Two -Dimensional Data

Here, we discuss the detection of fetal cardiac anomalies using 2D data. Cardiac fetal image databases acquired from various hospitals were used in this study. An Ensemble of neural networks was used for cardiac view identification and differentiation between the normal and abnormal hearts. These Models lead to automatic segmentation and help calculate fetal cardiothoracic measurements. It maintains high sensitivity for external imaging, with a high prevalence of CHD [39]. Supervised object detection depends on the CNN to detect cardiac structural abnormalities and substructures, and it performs better than other conventional anomaly detection algorithms [40]. The Mask RCNN architecture with ResNet50 as a backbone holds potential for the prediction of cord acidemia at birth [41]. The multistage residual hybrid attention module (MRHAM)-Yolo V4 slim model locates the four main chambers in fetal four-chamber views and outperforms current methods in detecting four cardiac structures in the FC plane [42]. The Sonography network, or Sono-Net, is the first real-time framework for the detection and bounding-box localization of views in freehand fetal ultrasound. This provides excellent results for the annotation of 2D ultrasound frames [43]. Deep learning label propagation with 3D residual U-Net segmentation is used for multilabel segmentation of fetal cardiac structures in CHD, and it achieves remarkable outcomes for subjects with aortic coarctation [44]. The Mask RCNN architecture was used for the segmentation of four fetal heart views, classification of the heart chamber and aorta in individual views, and detection of a hole in the septum in patients. It is an efficient procedure for partitioning heart views, classifying the heart chamber and aorta, and detecting holes in the heart septum [45]. The Unsupervised approach with an alpha-Gan network used for detecting hypoplastic left heart syndrome provides astonishing results and performs better than existing image anomaly detection methods [46]. The Convolutional and fully convolutional deep learning models are used to recognize the five screening views of the fetal heart, partition cardiac structures to evaluate fetal cardiac biometrics, and differentiate by a view among the normal hearts, Tetralogy of Fallot (TOF), and Hypoplastic Left Heart Syndrome (HLHS) as well as good computational efficiency [47]. V-Net with spatial dropout, group normalization, and deep supervision is used for the accurate segmentation of multiple views and abnormal conditions, which combines details from different perspectives and quickly loses structures owing to anatomical anomalies [48]. DW-Net, a cascaded convolutional neural network, is used to partition seven main anatomical structures in the apical four-chamber view [49]. The 2D Fetal Echocardiography dataare shown in Figure 4 [50].

Table 2. Overview of the application of deep neural networks in 2-D data for cardiac anomaly detection in the fetus

Author	**Methodology**	**objective**	**Datasets**		**Results**	**Merits**	**Limitation/ Future work**
[39]	Ensemble of neural networks	Cardiac view identification Differentiating the normal and abnormalhearts Models leading to automatic segmentation to compute fetal cardiothoracic measurements	**Training set**: 107,823 images taken from 1,326 echocardiograms. **Testing Set:** 4,108 fetal surveys		AUC-0.99, 95%-sensitivity 96%-specificity, and 100% NPV	Maintains high sensitivity on external imaging, sub-optimalimaging, imaging from fetal surveys, and fetal echocardiograms , on datasets.	To test and refine ensemble learning models in huge populations
[40]	Supervised object detection based on CNN	Detect cardiac substructures and cardiac structural abnormalities	**Cardiac substructure detection** Training data – 83 cases (191 videos,6122 images) Validation	**Cardiac structural abnormalities detection** Validation data – 8 cases (10 videos) Test data – 32 cases (42	AUC of Heart-0.787 Vessels - 0.891	SONO (Sonography) performed better than other algorithms in both datasets. It also reduces the cost and effort to collect data.	Difficulty to capture the isomerism, complete transposition of large vessels, and the changes in the cardiac substructures

			data - 11 cases (22 videos, 1009 images) Test data – 14 cases (34 videos, 1051 images)	videos) Validation data – 3 cases (10 videos) Test data – 11 cases (42 videos)			.
[41]	Mask RCNN architecture with ResNet50 as a backbone	Septal defects detection using instance segmentation	764 - fetal heart images 693 images - for training, validation, and testing 71 images- normal conditions		Multiclass detection of the heart chamber, with 97.59% - right atrium 99.67% - left atrium, 86.17% - left ventricle, 98.83% - right ventricle 99.97% - aorta	MCNN holds the potential for the prediction of cord acidemia at birth	To implement hybrid approaches to CTG interpretation
[42]	MRHAM-Yolo V4 – slim model	Locates the 4 important chambers in fetal Four Chamber views.	PASCAL VOC dataset and CIFAR -10 and CIFAR -100 datasets		Precision-0.919 Recall – 0.971, F1 score - 0.944, mAP-0.953,	MRHAM-YOLOv4-Slim model surpasses present methods in predicting four cardiac structures in the FC plane.	To outline an automatic classification model to automatically diagnose the fetal heart
[43]	Sonography network or SonoNet	First real-time framework for detection Bounding box localization of standard views in freehand fetal ultrasound.	2D ultrasound examinations of 2694 volunteers		F1-score-0.798 Accuracy for retrospective frame retrieval – 90.09%. Accuracy for localization - 77.8%	It achieves astonishing results for real-time annotation of 2D ultrasound frames.	To comprehend the temporal dimension in the training and prediction for fetal cardiac videos.

[44]	Deep-learning label propagation with 3D residual U-Net segmentation	Multilabel segmentation of fetal cardiac structures in CHD	40 fetal subjects with suspected coarctation of the aorta (CoA)	Dice score - 0.79±0.02	It achieves astonishing results for subjects with coarctation of the aorta,	To extend the framework to target other cardiac anomalies.
[45]	Mask RCNN architecture	Segmentation and classification of the heart chamber and aorta. Detection of the hole in the septum.	1149 fetal heart images for the identification of four shapes of the fetal heart and standard views containing 24 objects heart chambers in each view containing 17 objects and three cases of CHD	Intersection over union – 99.7% Dice coefficient similarity – 89.70% Mean average precision - 98.30% and 82.42% for variationof intra and inter-patient.	It is an effectual technique of segmenting heart views, differentiating the heart chamber, and predicting the hole.	To test and clarifymodels in huge populations
[46]	Unsupervised approach with Alpha-Gan Network	Detecting Hypoplastic left heart syndrome	2D fetus ultrasound images of the four-chamber view	0.81 - AUC	Promising results and better performance	To make full video sequences and robust time series analysis
[47]	Convolutional and fully convolutional deep learning models	(i) Detect the five canonical screening views of the heart and (ii) Partition cardiac structures to measure the biometrics (iii) differentiate by perspective between normal hearts, TOF, and	685 retrospectively gathered echocardiograms	TOF sensitivity - 75% specificity - 76%, normal vs. HLHS sensitivity-100% and specificity - 90%	Good computational efficiency	To improve the model by training in more studies and improving the neural network architecture

		HLHS				
[48]	V-Net with spatial dropout	Accurate segmentation in multiple views and abnormal conditions	2D fetal echocardiographic dataset with 199 normal and 100 abnormal cases	an average Dice score - of 79%.	This framework assimilated details from a variety of views and is clear to structures missing due to structural anomalies	Not mentioned
[49]	DW-Net, a cascaded convolutional neural network	Segments seven essential anatomical structures in the A4C views.	A large count of fetal echocardiography images with different angles of scanning was obtained by various clinicians from all over China.	Dice Similarity Coefficient (DSC) - 82.7% Pixel Accuracy (PA) – 93.3% AUC – 99%	Not mentioned	Not mentioned

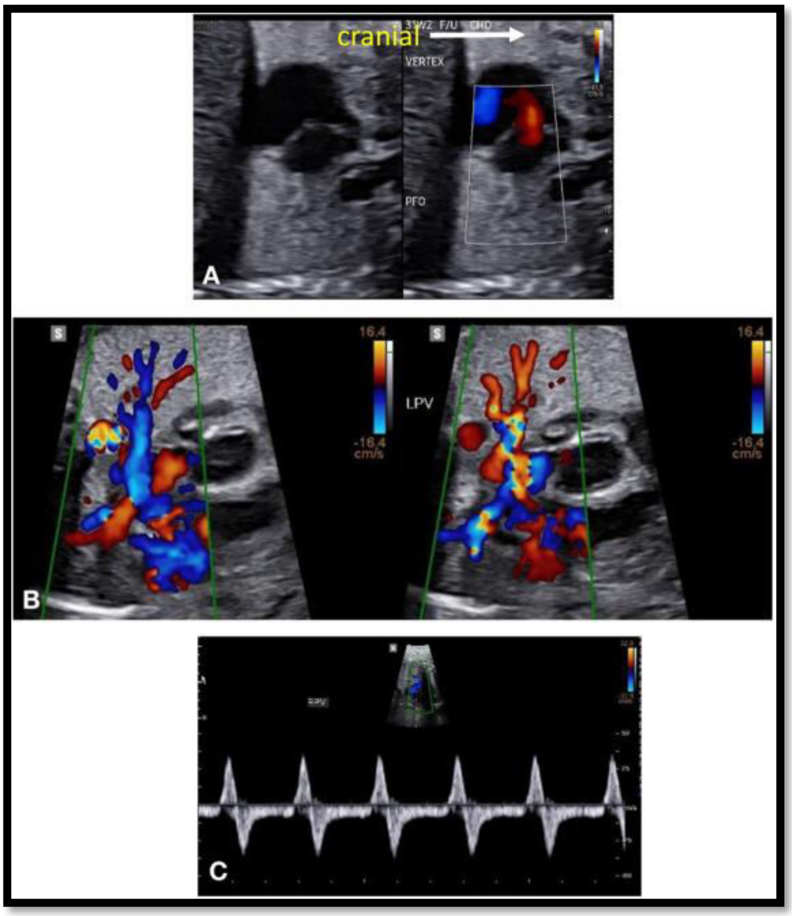

Fig: 4 Representation of 2D Fetal Echocardiography data

3.3 Three-Dimensional cardiac fetal data

Here, we discuss fetal cardiac anomaly detection using 3D data. The databases are mostly fetal ultrasound videos. The Faster RCNN method is used for the detection of the aorta, and this method performs best in detecting the aorta [51]. The Temporal fetal heart network (Temporal HeartNet) precisely describes detailed heart parameters and acquires astonishing results on a real-world clinical dataset [52]. The Novel knowledge transferred to the CNN was used to detect standard planes from US videos and was efficient, providing the best results [53]. The Cropping-Segmentation-Calibration method was used for the detection and partitioning of the ventricular septum in fetal ultrasound videos and achieved the best results [54]. The CNN method using the U-net architecture was used to detect fetal cardiac standard planes and segmentation, and it showed substantial enhancement in segmentation accuracy compared to the representative segmentation method [55]. An Automated framework with a multiclass discriminative classifier and conditional random field model was used for the detection of heartbeat and fetal presentation, providing the best classification performance [56]. A Fully convolutional neural network that detects the fetal heart classifies discrete frames as connected to any of the standard viewing planes, and produces a lower error rate in real-world clinical ultrasound data [57]. Sample 3D ultrasound images of fetal heart are shown in Figure 5 [58].

Table 3. Overview of the application of deep neural networks in 3D data for cardiac anomaly detection in the fetus

Author	Methodology	objective	Datasets	Results	Merits	Limitation/Future work
[51]	Faster RCNN (Regional Convolutional Neural Network) method	Detection of aorta	Ultrasound videos containing a four-chamber view of the fetal heart	mAP value - 83.71%.	Performs best in detecting aorta	Not mentioned
[52]	Temporal fetal heart network (Temporal HeartNet)	Accurately represents detailed heart parameters.	91fetal cardiac screening videos from 12 subjects	An error of 21.6% Shows that it is constant than human annotators	Achieves expert results on a real-world clinical dataset	To use a more advanced methods.
[53]	Novel knowledge transferred convolutional neural network	To predict standard planes from US videos	Ultrasound videos of pregnant women (fetus gestational age 18 to 40 weeks)	Accuracy – 90.8% Precision- - 74.8% Recall- 74.7% F1-score – 74.7%	Efficient detection provides the best results	To extend the prediction of other US standard planes or structures of anatomy.
[54]	Cropping-Segmentation-Calibration (CSC)	Detection and partitioning of the ventricular septum in the fetus	615 frames from 421 normal fetal cardiac ultrasound videos	Achieves best results	Not mentioned	Not mentioned

[55]	CNN method using U-net architecture	To detect cardiac standard fetal planes and segmentation	519 images of fetal cardiac obtained from 3 videos	mIoU of Deep Lab v3+ - 0.0224 U-net - 0.1519 CSC - 0.5543	CSC showed significant development in accuracy contrasting with other methods	To evaluate the algorithm and the automatic detection of ventricular septal abnormalities and the automatic measurement of cardiac axis
[56]	Automated framework with multiclass discriminative classifier and conditional random field model	detection of fetal presentation and heartbeat	323 videos were obtained from subjects.	Overall Accuracy - 93.1%	Provides the best classification performance	To use a larger dataset of ultrasound to build a strong classifier
[57]	Fully convolutional neural network	predicting the fetal heart differentiating every single frame	91 ultrasound videos	The classification error rate of 23.48%	FCN model produces less error rate in real-world clinical ultrasound data.	To use the temporal details in video to develop accuracy and to decide the state of cardiac details.

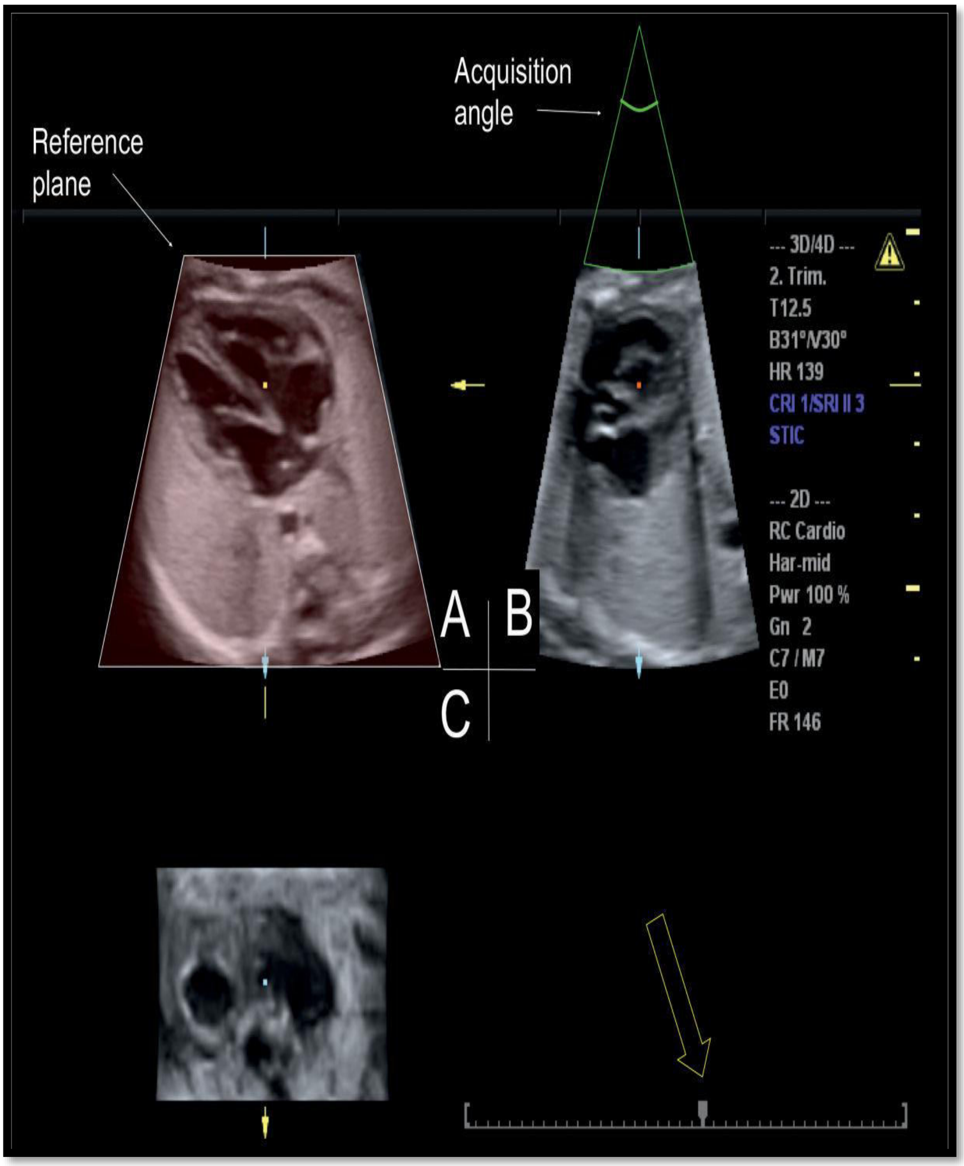

Fig: 5 Representation of 3DUltrasound of the Fetal Heart

Discussion

The primary motivation for this study arises from the urgent need to enhance the accuracy and reliability of fetal cardiac anomaly detection. Traditional methods often rely on manual analysis by trained specialists, which can be time consuming and subject to human error. Furthermore, with the increasing volume of prenatal imaging data, the demand for automated high-throughput diagnostic tools is growing.

Overall, here we discuss about the results obtained by the application of deep learning techniques for the anomaly detection in the 1D, 2D and 3D data of the fetus.The studies regarding 1D data for anomaly detection in fetus suggests that deep learning models can be effective in detecting fetal state conditions using various types of data, such as CTG recordings having fetal heart rate signals and ECG signals. Each model performs differently based on the evaluation metrics and tasks designed to be solved. However, based on the results reported in Table 1, some methods achieved higher accuracy than others did. For example, the 1-D CNN model used for the fetal state condition achieved 97.46% accuracy, and the anomaly detection model using improved Anomaly Generative Adversarial Networks (AnoGAN) achieved an AUC of 0.9475 and F-measure of 0.9143.

In recent years, deep learning techniques have been used to detect fetal heart anomalies from ultrasound images. Various studies on 2D data for anomaly detection in fetuses have used different deep learning architectures to detect different cardiac substructures such as septal defects, four important chambers, and the aorta (Table 2). An ensemble of neural networks was used for cardiac view identification, and differentiating between normal and abnormal hearts showed good performance, with an AUC of 0.99, sensitivity of 95%, specificity of 96%, and negative predictive value (NPV) of 100%.. Similarly, the mask RCNN with ResNet 50 as the backbone architecture was used to detect septal defects using instance segmentation. It achieved multiclass detection of the heart chamber with high precision and recall values. Another study using SonoNet achieved an F1-score of 0.798 and a high accuracy for retrospective frame retrieval and localization. Furthermore, an unsupervised approach with the Alpha-Gan Network was used to detect Hypoplastic Left heart syndrome, achieving promising results and better performance. Future work in this field can be performed using hybrid approaches to CTG interpretation and extending the existing frameworks to target other cardiac anomalies.

Studies regarding 3D data have discussed the application of deep learning techniques in fetal cardiac ultrasound screening and are presented in Table 3. Overall, the results showed promising performance in detecting specific structures of the fetal heart such as the aorta, ventricular septum, and fetal heart plane. The Faster RCNN method performed best in detecting the aorta, whereas the Temporal HeartNet accurately represented the detailed heart parameters. However, based on the reported results, it appears that the Cropping-Segmentation-Calibration (CSC) method achieves the best results for detecting and partitioning the ventricular septum in the fetus. Additionally, the CNN method using the U-net architecture showed an improvement in accuracy compared to other methods for detecting cardiac standard fetal planes and segmentation. Each method has its merits and limitations. Future work should be conducted to improve the performance of these methods, such as by using larger datasets or developing more advanced training strategies.

Conclusion

In this review, we discuss various fetal cardiac anomalies and compare deep-learning techniques applied to 1D, 2D, and 3D data. The reviewed papers spanned the period from 2009 to 2025. We provide an overview of the datasets used and the results obtained through different deep learning methodologies, highlighting the advantages, shortcomings, and potential future work for each method. The detailed evaluation metrics are also discussed. For instance, a 1D CNN model achieved 97.46% accuracy in detecting fetal state conditions, whereas a recurrence plot CNN achieved 98.6% accuracy in detecting fetal hypoxia. For 2D data, an ensemble of neural networks achieved an AUC of 0.99 for detecting cardiac substructures, and the Mask RCNN excelled in multiclass detection tasks. For 3D ultrasound data, the CSC method yielded superior results in detecting and partitioning the ventricular septum, provides an elaborate review, and serves as a valuable resource for researchers to find the most suitable algorithms for fetal cardiac anomaly detection in 1D, 2D, and 3D data. Future work will include using larger and more diverse datasets, developing advanced training strategies, and implementing real-time analysis for immediate feedback during examinations.

Conflict of Interest

None

Data Availability

None

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