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Research Article

Detection of Prenatal Cardiac Disease using Computer Vision and Artificial Intelligence

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Abstract: Prenatal cardiac anomalies, commonly referred to as congenital heart defects (CHDs), comprise a spectrum of pathologies that adversely affect cardiac function. There is a correlation between the numerous risks of cardiovascular diseases and the pressing requirement for precise, reliable, and efficient methods of early detection. The contemporary epoch of voluminous data presents a plethora of novel prospects for clinicians to utilize artificial intelligence in order to identify and enhance treatment for pediatric patients and those afflicted with congenital heart disease. Machine learning, a prevalent technique in the field of artificial intelligence, has been utilized to forecast various outcomes in obstetrics. The application of artificial intelligence in real-time electronic health recording and predictive modelling has demonstrated promising outcomes in the domain of fetal monitoring. The present research provides an in-depth review of recent advancements and challenges in the application of artificial intelligence techniques, such as deep learning and computer vision, for the detection of congenital heart disease.

***Keywords*:** artificial intelligence, congenital cardiac defect, image processing, deep learning

MSC: 68T01, 68T05, 68T45

1. Introduction

Congenital heart disease (CHD) refers to a group of conditions characterized by structural as well as operational heart and blood vascular abnormalities present at conception. It compromises the heart's anatomy and functioning, making it a common congenital defect that threatens the well-being of newborns [1]. The timely identification and diagnosis of CHD can potentially enhance the longevity and well being of afflicted pediatric patients. As per the World Health Organization (WHO), there are more than 18 million fatalities each year attributed to heart ailments, encompassing coronary heart disease and cerebral stroke, with 82% of these deaths being caused by such conditions. High mortality rates are prevalent in rural areas [2]. Therefore, early detection of fetal cardiac abnormalities, preferably before delivery, may substantially enhance prognosis and minimize further sickness and morbidity. The detection of CHD through traditional means involves the hands-on assessment of cardiac visuals, a process that is susceptible to oversights and subjectivity and can be time-intensive [3]. However, detection of this type of cardiac condition is only possible through the use of ultrasound imaging,

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which does not always produce correct data. The ultrasound imaging technique assesses the structural and functional aspects of the heart during the prenatal stage to facilitate the detection of congenital heart disease [4] and myocardial disorders [5]. The past few years have seen a meteoric rise in the incorporation of artificial intelligence (AI) into our daily lives. The utilization of computational intelligence has the capacity to aid healthcare professionals in identifying signs of CHD through the provision of automated and precise analysis of cardiac images. The medical industry has been slower to adopt AI, despite findings indicating the technology's exceptional efficacy when applied to a specific, clear clinical job [6]. The diagnosis process for congenital cardiac abnormalities has been enhanced thanks to recent developments in AI in medical fields. As a result, several algorithms based on AI have been devised to identify CHD from echocardiography visuals accurately. Survival rates for those born with CHD have increased along with advances in treatment and surgery, leading to an expanding number of adults with CHD [7]. AI has the potential to enhance the care and treatment of such patients in a number of ways. Figure 1 represents the explainable AI technology as a tool to assist in detecting prenatal cardiac condition.

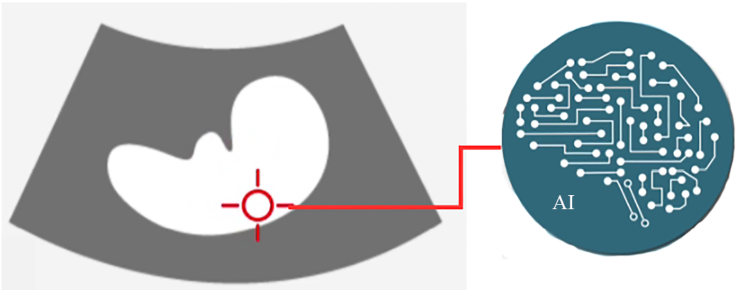


Figure 1. Explainable AI technology as a tool to assist in detecting prenatal cardiac condition [3]

Experts from Japan are working to find a solution to this issue by seeking the assistance of computational intelligence. Most significantly, they assist medical professionals responsible for patient care in better comprehending the process by which AI systems identify cardiac problems [8]. The utilization of AI enables the analysis of ultrasound recordings depicting fetal cardiac activity, both in normal and anomalous states. This technology can subsequently facilitate the identification of potential structural imperfections in newly acquired embryonic cardiac recordings. Auscultation has been enhanced in terms of accuracy for screening valvular and congenital heart disease through the utilization of smart technology [9]. The utilization of artificially intelligent systems by medical practitioners can be advantageous in delivering the best possible treatment to patients suffering from this type of condition. This is due to the availability of comprehensive and varied data sets covering intricate disease diagnosis and management and multimodality imaging [10]. The capacity of various AI methodologies, in conjunction with genomic data, to detect modified gene pathways that play a crucial role in the emergence of congenital heart anomalies has been evaluated by scholars [11]. Despite the potential benefits, a significant number of medical practitioners remain hesitant to embrace this methodology due to the "black box" issue. The intricate rules governing the AI's decision-making process are so convoluted that its creators and other people frequently struggle to comprehend the underlying reasoning. A team of scholars from the RIKEN Center for Advanced Intelligence Project and their collaborators investigated the AI decision-making process. The objective of the researchers was to generate a graphical depiction of the choices made by their artificial intelligence system [8]. This depiction could subsequently be utilized to bolster the ultrasound screening procedure in the medical facility. While additional research that encompasses diverse ultrasound instruments, as well as information, is necessary, the findings underscore the potential advantages of AI technology for both patients and medical practitioners. Moreover, the outcomes could aid in healthcare experts' acceptance of this system by providing insight into its workings. This study offers a comprehensive synopsis of the latest developments and obstacles encountered using artificial intelligence methodologies, including deep learning and computer vision, to detect congenital heart disease. Additionally, we examine potential avenues for advancing and exploring AI-driven prenatal heart disease recognition. Therefore, section II discusses the implementation of AI in the medical field after the introduction in section I. In the third section, we talked about the numerous congenital cardiac problems. The subsequent section delved into diverse image modalities and pre-processing methodologies. The following section entails a discussion of diverse approaches for detecting CHD. There are various limitations and challenges in this field of disease detection. Some of them are presented in section VI. Section VII concludes the article.

2. Artificial intelligence in medical care field

The implementation of AI is gradually renovating the terrain in medical care and research. In recent times, medical-image technology for diagnosis has broadened the scope of computational intelligence to encompass domains formerly exclusive to human specialists [12–14]. Applications of field of AI in Biomedical research and diagnostic works are shown in Figure 2.

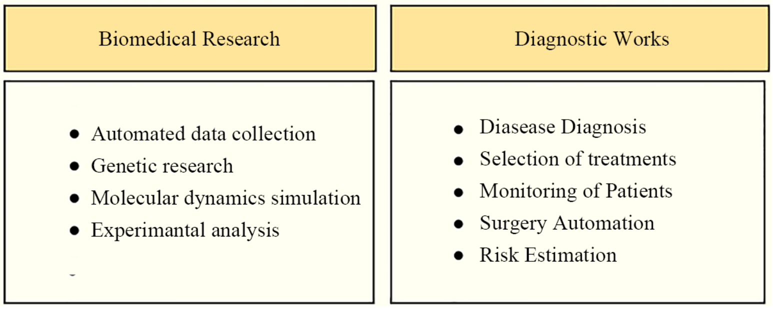


Figure 2. Contemporary and possible application filed of AI in Biomedical research and diagnostic works

During the 1970s, rule-based methodologies achieved considerable accomplishments and have demonstrated their ability to analyze electrocardiograms, identify illnesses, select suitable therapies, offer explanations for clinical explanations, and aid medical professionals in formulating screening speculation for intricate patient scenarios [15]. Despite their effectiveness, rule-based applications can be expensive to construct and may lack flexibility, as they necessitate the explicit articulation of decision rules and rely on human-authored developments. Furthermore, the encoding of higher-order connections among various pieces of understanding contributed by different professionals poses a challenge, and the extent of pre-existing medical expertise constrains the effectiveness of the structures. In addition, the implementation of a system that combines predictable and probabilistic logic to limit pertinent clinical context effectively, give priority to diagnostic theories and suggest therapy posed a challenge.

In contrast to the initial wave of AI systems dependent on medical professionals' expertise for collecting information and establishing reliable decision rules, contemporary AI study has adopted machine-learning techniques capable of detecting intricate relationships within data sets. This approach enables the identification of patterns that may have been previously overlooked. Based on the specific tasks they aim to address, fundamental machine learning algorithms can be broadly classified into two groups, namely supervised and unsupervised. Supervised techniques operate by gathering a substantial quantity of "training" instances, which encompass inputs and the intended output labels. Through the examination of the patterns present in all of the designated input-output pairs, the algorithm acquires the ability to generate the accurate output for a specific input in novel instances.

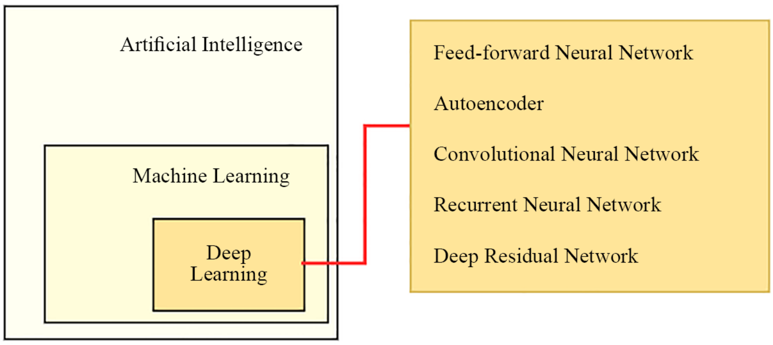


Figure 3. Various deep learning networks

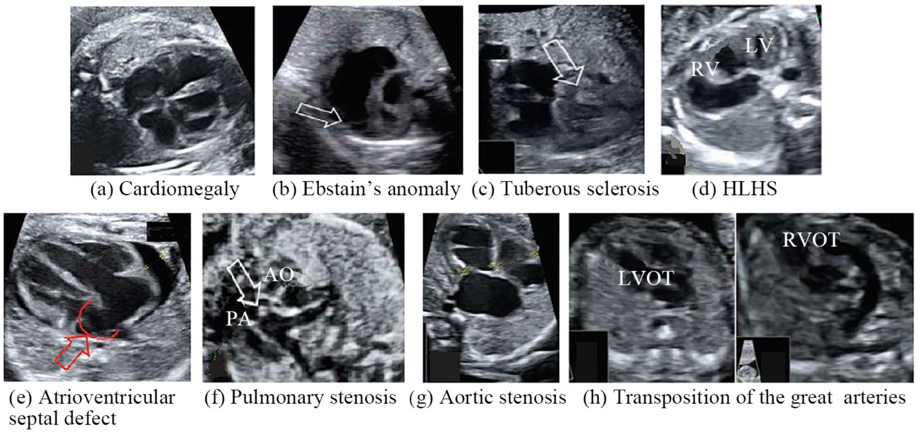


Figure 4. Different congenital cardiac condition visuals [5]

The utilization of neural networks comprising numerous layers is capable of effectively representing intricate relationships between input and output. However, this approach may necessitate a larger dataset, increased computational resources, or sophisticated architectural designs to attain optimal performance. The utilization of computational power, vast datasets, and convolutional neural networks (CNNs) has resulted in a significant transformation of not only medical image analysis but also the entire domain of computer vision, thanks to deep learning. CNNs employ a distinct layer that serves to condense and modify groups of pixels within images, with the aim of extracting features of a more abstract nature. Prior to the emergence of CNNs, it was necessary to establish and derive features from images, with the efficacy of machine learning algorithms being contingent upon the calibre of such attributes [16]. The CNNs represent a significant advancement in image processing as they are capable of processing raw images and acquiring important characteristics from the training data. This feature simplifies the training process and streamlines the recognition of picture sequences. This deep learning algorithm has demonstrated its significance in the triumph of deep learning in the field of image analysis. Furthermore, they have played a pivotal role in the subsequent transformation of medical imaging. A continuous communal endeavour is underway to aggregate neural network implementations in the fields of biology and medicine [17]. Figure 3 illustrates the various deep learning models.

The resurgence of AI in recent times can be largely attributed to the efficacious utilization of deep learning. This technique entails training an artificial neural network comprising multiple layers on extensive datasets. The application of deep learning has demonstrated significant advancements in the domain of image categorization tasks. The fundamental structure of deep neural networks comprises an input layer and an output layer, with several intervening hidden layers. The perceptron and feed-forward neural networks are considered to be rudimentary architectures in the field of neural networks. Autoencoders are utilized in the process of dimensionality reduction. On the other hand, sparse autoencoders have the ability to produce valuable supplementary features. Recurrent neural networks have been found to be a valuable tool in processing time-series data. The performance of conventional deep feed-forward neural networks has been enhanced by the incorporation of connection skips in deep residual neural networks, which effectively prevent model efficiency saturation.

3. Congenital heart conditions

A congenital heart defect is one that is present at birth and results from abnormal development of the heart of an unborn child while the mother is pregnant. Various visuals of congenital cardiac conditions are shown in Figure 4. The prevalence of congenital cardiac problems is highest among all types of birth defects. These cardiac conditions are categorized into various classes by professionals in this field. One such factor is blood flow. Cardiac anomalies can impact fetal blood flow. The potential conditions that may arise in the blood flow of an individual as a result of this factor are:

- The reduction of flow speed.
- Deviation from the intended course.
- Blocked flow.
- Insufficient oxygenation to facilitate systemic circulation.

As a result of the aforementioned factors, the fetal heart may develop a range of congenital heart diseases. Some of them are discussed below.

3.1 *Coarctation of the aorta (CoA)*

The aorta exhibits stenosis or constriction. This phenomenon results in impeded blood circulation to the lower extremities and a subsequent rise in blood pressure proximal to the narrowing. Typically, neonates do not exhibit any noticeable symptoms upon delivery. However, manifestations may arise as early as within the initial week of life.

3.2 *Aortic stenosis (AS)*

The aortic valve between the left ventricle and the aorta exhibits inadequate formation and constriction. This condition poses a challenge for the cardiovascular system to circulate blood throughout the body effectively. A typical valve is composed of three leaflets or cusps, whereas a stenotic valve may exhibit a reduction in the number of cusps to one or two.

3.3 *Pulmonary atresia*

The pulmonary valve exhibit underdevelopment. Valve complications with growth impede the passageway of leaflets, thereby impeding the forward circulation of blood coming from the right ventricle to the lungs.

3.4 *Transposition of the great arteries*

When this occurs, the aorta and pulmonary artery switch places. As a result, the aorta develops from the heart's right atrium. Most of the oxygen-depleted blood pushed back out from the heart bypasses the lungs entirely.

3.5 *Atrial septal defect (ASD)*

The right and left atrium, the heart's upper chambers, are separated by a hole. Because of this, the heart's blood flow becomes erratic. It is possible that some subjects may show no signs and seem completely normal.

3.6 *Ventricular septal defect (VSD)*

The ventricular septum (the wall separating the two lower ventricles) develops a hole. As a result of the increased pressure in the left ventricle, blood can flow back into the right ventricle through this hole. This results in the right ventricle pumping excessive blood into the lungs, which can lead to respiratory distress due to obstruction.

3.7 *Cardiomegaly*

Cardiomegaly refers to an enlarged heart beyond its normal size. In this instance, the myocardium may exhibit abnormal hypertrophy or dilation.

3.8 *Combination cardiac defects*

There are occasions where several cardiac abnormalities coexist. The resulting issue is more nuanced and may have origins in more than one of these areas. Two of these types of defects are- atrioventricular canal and hypoplastic left heart syndrome (HLHS).

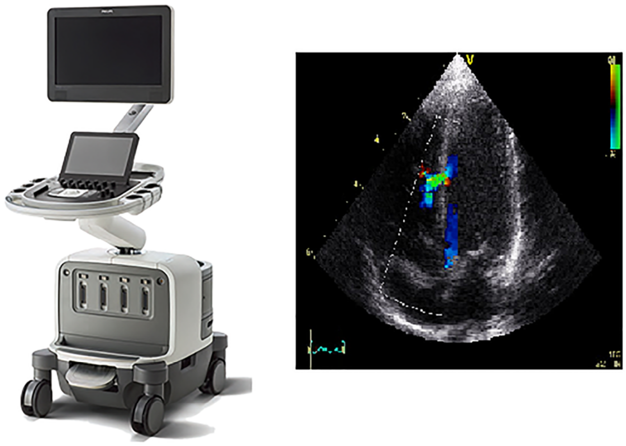
4. Image modalities and pre-processing techniques in chd detection

The utilization of cardiac imaging is of immense value in the comprehensive handling of CHD across all phases of medical care. The progressions made in the arena of this type of imaging have made a major contribution to the enhancement of medical results in this domain. Echocardiography continues to be the primary visualization medium. Computerized tomography (CT) and MRI are non-intrusive descriptive imaging techniques that complement in-detail assessments. These imaging modalities are becoming more prevalent in the detection and monitoring of individuals with congenital heart defects.

4.1 *Image modalities*

4.1.1 *Echocardiography*

Concurrent with the progress of technology that allows for comprehensive cardiac evaluation during the latter part of the first trimester, a subset of individuals may be susceptible to fetal cardiac ailments that can be detected between the 11th and 14th week of pregnancy. A significant obstacle in the exploratory analysis of CHD pertains to the creation of cardiovascular testing equipment that possesses both high resolution and high throughput capabilities. These tools are necessary to identify structural cardiac defects in neonates accurately. The predominant modality employed for the detection of congenital cardiac conditions is 2D ultrasound echocardiography [18, 19]. The methods utilized for conducting prenatal echocardiography encompass transabdominal and endovaginal techniques. The transabdominal approach is typically sufficient for most women beyond 12 weeks of pregnancy to acquire a comprehensive embryonic echocardiogram [20]. The potential for transvaginal echocardiography to yield supplementary data beyond what can be obtained through transabdominal echocardiography is contingent upon the proximity of the fetal cardiac organ to the cervix [21]. A picture of echocardiography for CHD detection is shown Figure 5.



(a) (b)

Figure 5. Echocardiography for CHD Detection: (a) The Philips EPIQ 7, which is used for premium ultrasound; (b) an anomalous cardiac condition found via echocardiogram [8]

4.1.2 *Magnetic resonance imaging (MRI)*

A persistent requirement exists for a dependable mode of supplementary imaging, especially in scenarios where a more comprehensive 3D vascular visualization is necessary or when the screening performance of ultrasound windows is suboptimal. The application of 3D echocardiographic procedures to fetal cardiology, specifically spatiotemporal image correlation imaging (STIC), is subject to analogous constraints as those encountered in 2D echocardiography. Additionally, fetal motion can pose a challenge to the acquisition of accurate images. Therefore, these methodologies exhibit inadequate dependability in the context of clinical application [22].

The MRI, a widely recognized modality for examining various organ systems [23], is significantly vulnerable to fetal motion, specifically in the context of 3D imaging [24]. The MRI technology provides the necessary spatial and temporal resolution to accurately detect crucial anatomical features frequently employed in diagnosing fetal cardiac conditions [25]. The steady-state free-precession (SSFP) sequence holds significant importance in fetal heart MRI due to its ability to provide superior contrast within blood flow, which exhibits hyper-intensity and hypo-intensity [26]. The study conducted by Kainz et al. employed rapid rotation invariant spherical harmonics picture indicators in conjunction with random forest ensemble learning techniques to locate the spinal cord. The study also demonstrated an effective approach to produce an identification of the fetal lung based on this data, utilizing two distinct MRI field strengths. The study aimed to develop a semi-automated technique for analyzing the fetal thorax using authentic 3D volumes [27]. Amerom et al. were able to produce a four-dimensional representation of the fetal heart through the utilization of a multi-planar real-time balanced steady-state free precession acquisition that was highly expedited. This was accomplished by combining retrospective image-domain methodologies for the purposes of movement rectification, cardiac coordination, and outlier refusal [28].

4.1.3 *Cardiac computed tomography (CCT)*

The utilization of cardiac computed tomography (CCT) has observed a surge in its application for evaluating individuals, both pediatric and grownups, diagnosed with CHD. This trend can be attributed to the technological advancements in CCT and the growing incidence of adult patients with palliated CHD. In difficult situations that need exploration of coronary vessels or intricate vascular and thoracic anatomy, it is often suggested to do this procedure. The procedure functions as a supplementary technique to fetal ultrasound and cardiovascular MRI. CCT has the potential to offer distinctive medical insights while being comparatively simpler to perform and less reliant on sedatives in contrast to alternative techniques [29]. MRI is the preferred approach for monitoring complex CHD due to its non-ionizing radiation properties. Additionally, the MRI technique has the capacity to measure vessel flows and ventricular functioning, as well as detect myocardial fibrosis. Compared to conventional MRI, CCT has the benefit of submillimeter isotropic spatial accuracy, rapid scanning instances, and high-quality images unaffected by ferromagnetic aberrations among individuals who have undergone previous treatments [30]. The utilization of CCT technological advancements has significantly altered the entire diagnostic risk assessment for modern imaging in CHD, resulting in a notable shift towards CCT as a customary visualization examination in this patient group [31].

4.1.4 *Nuclear scintigraphy*

Nuclear cardiology is a physiological diagnosing technique employing radioisotope-annotated substances to image and measures cardiac functioning, blood circulation, perfusion and viability [32]. It is a diagnostic modality that employs minute quantities of radioactive tracers to identify pathologies affecting skeletons, connective tissues, and blood vessels. It is feasible to affix said particles onto drivers that exhibit an affinity for bone lesions, soft tissue malignancies, and locations of infection. The radiopharmaceutical agent ultimately accumulates in the region of interest within the organism under investigation, where it emits gamma radiation energy. The aforementioned energy can be tracked through the utilization of a device commonly referred to as a gamma camera. These instruments collaborate with a computer system to quantify the quantity of radiotracer assimilated by the human body during the examination and to generate distinctive images that provide information on the configuration and operation of structures and other internal bodily components [33]. This highly delicate methodology has the potential to identify ailments that may not be discernible through alternative imaging modalities. In comparison with echocardiography, nuclear scintigraphy has been shown to be a less accurate method for evaluating the heart's structure and functioning [34].

4.2 *Pre-processing techniques*

The practice of image pre-processing involves the preparation of data to suit a specific operation. The primary objectives of medical image pre-processing entail mitigating photographic acquisition and normalizing images throughout a given data set. Due to various inconsistencies in images and other signal-based data types utilized for prenatal cardiac condition detection, numerous pre-processing techniques have been explored by scholars. Pre-processing techniques such as background removal, denoising, resampling, intensity normalization, and data annotation are commonly employed in the domain of CHD detection for the purpose of refining acquired data. The pre-processing techniques for CHD detection is shown in Table 1.

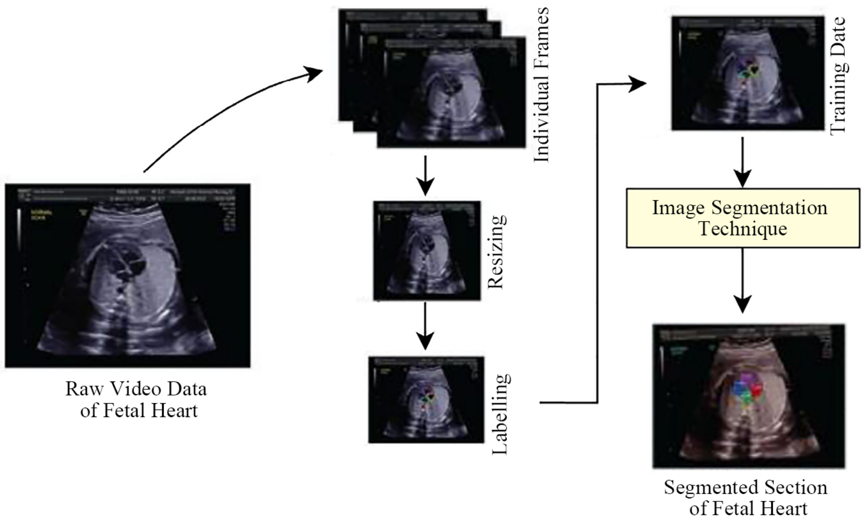


Figure 6. Application of pre-processing and image segmentation techniques to fetal heart image frames

The process of background removal entails the partitioning of the area of interest from the surrounding backdrop in an image. Restricting the picture to a specific area of importance can enhance the effectiveness and precision of the intended workflow. This particular step is discussed in the image segmentation of the fetal heart subsection in detail.

Table 1. PRE-processing techniques for chd detection

Authors	Ref.	Data	Pre-processing method
Wang et al.	[35]	PCG signals	Normalization and denoising
Sampath et al.	[36]	Ultrasound images	Probabilistic patch-Based maximum likelihood estimation
Dozen et al.	[37]	Time-series video data	Pixel-by-pixel annotation, unified image format
Sapitri et al.	[38]	2D ultrasound videoframe	Resizing, ground truth, data augmentation
Nurmaini et al.	[39]	Ultrasound images	Frame form processing

Medical imaging techniques are prone to noise, which causes unpredictable variations in the intensity of a picture. In order to mitigate noise, scholars have the ability to apply spatial and frequency domain filtering techniques to pictures [35]. Even machine learning or deep learning methods can be applied to denoise ultrasound images or other signals. Resampling can be utilized to modify the pixel size of a picture while preserving its spatial boundaries within the patient's coordinate frame. The process of resampling is a valuable technique for achieving uniformity in picture quality within an archive that comprises pictures obtained using various scanning devices. The process of picture quality normalization involves the standardization of picture intensity readings within a given dataset. While the act of displaying image data through a screen alters the perception of the data, intensity normalization involves the modification of the picture's values themselves. Frequently, it has been observed that the primary format of the gathered images is Digital Imaging and Communications in Medicine (DICOM), which is the currently accepted norm for medical photographs. Different researchers employ diverse techniques to transform the picture format to meet the specifications, as DICOM is incompatible with the input data format of most localization models. The localization of medical images is a crucial area of focus within the field of medical image processing and analysis, representing a significant step in the subsequent analysis of such images. The expertise of medical practitioners predominantly influences the segmentation of medical images using conventional methods. The basic flow diagram of fetal cardiac defect segmentation methodology is illustrated in Figure 6. The growing frequency of computer-aided diagnosis has led to its gradual application in the field of medical image segmentation. Imaging has been found to be a valuable tool in the field of fetal cardiology, aiding in the identification and surveillance of fetuses exhibiting cardiovascular compromise that may be linked to various fetal pathologies. Various ultrasound techniques are presently employed for assessing fetal cardiac structure and function. These include standard two-dimensional imaging, M-mode imaging, and tissue Doppler. Nevertheless, the evaluation of the newborn heart remains a complex task primarily attributable to the involuntary motions of the developing baby, the heart's limited dimensions, and the insufficient proficiency in fetal ultrasound among certain sonographers. Hence, the utilization of new methods to enhance the elementary obtained pictures, facilitate the extraction of observations, or assist in the identification of cardiac anomalies is of significant significance for the optimal evaluation of the infant's heart during pregnancy. In contemporary times, machine learning techniques, particularly deep learning techniques that rely on CNNs, have demonstrated noteworthy advancements and accomplishments within the realm of computer vision. The aforementioned techniques are also utilized in the context of segmenting medical images [36]. The advent of the U-Net network has garnered significant interest in the research and implementation of deep learning techniques utilizing deep convolutional neural networks for medical image segmentation [40]. Cropping-Segmentation-Calibration (CSC) is a new localization approach that was developed by Dozen et al. for use in ultrasound motion pictures. It is tailored specifically to the ventricular septum. The output of the U-net is calibrated by the CSC using the time-series data from clips as well as particular segment metadata [37]. Sengan and colleagues proposed an innovative V-Net architecture, known as Attention-Residual Network-based V-Net (ARVNet), to achieve precise localization of the heart of a newborn and detect any potential fundamental cardiac anomalies [41]. Unified deep convolutional and recurrent frameworks enable the comprehension of fetal echocardiography footage by incorporating segmented temporal and spatial characteristics of distinct anatomy-based structural components within a broader spatiotemporal environment [42]. The segmentation techniques proposed by various authors are illustrated in Table 2.

Table 2. Segmentation techniques for chd detection

Authors	Ref.	Data	Segmentation method
Wang et al.	[35]	PCG signals	Discreet wavelet transform + Hadamard product
Sampath et al.	[36]	Ultrasound images	Fuzzy-connectedness
Dozen et al.	[37]	Time-series video data	Cropping-Segmentation-Calibration
Sengan et al.	[41]	4CH view dataset	ARVNet
Patra et al.	[42]	Echocardiography video data	Spatio-temporal anatomy segmentation
Sapitri et al.	[38]	2D ultrasound videoframe	U-Net
Jafari et al.	[43]	AP4 echo cines	T-L network + U-Net
Hu et al.	[44]	4C view echocardiography	BiSeNet
Shozu et al.	[45]	Fetal ultrasound videos	Multi-frame cylinder approach
Yang et al.	[46]	4C view echocardiography	DeeplabV3+
Nurmaini et al.	[39]	Ultrasound images	Mask-RCNN
Rachmatullah et al.	[47]	Ultrasound video data	U-Net + Otsu threshold

Jafari et al. presented a semi-supervised machine-learning technique that utilizes data without labels to enhance the efficacy of left ventricle localization systems [43]. The Bilateral Segmentation Network (BiSeNet) was suggested by Hu et al. as a means of completely automating the localization of pediatric echocardiography images in the 4-ventricle viewpoint. The BiSeNet model is comprised of two distinct pathways: a spatial pathway designed to capture low-level spatial characteristics, and a context-based pathway intended to leverage high-level semantic attributes. Moreover, an algorithm for feature amalgamation is employed to integrate the attributes acquired from both pathways [44].

5. CHD detection methods

The implementation of prenatal screening for CHD has the potential to enhance neonatal outcomes and provide avenues for pre-birth treatments, post-birth surgical procedures, or other forms of medical intervention. While recent meta-analyses have shown an acceptable sensitivity and high particularity for fetal echocardiography when performed by experienced professionals, the accuracy of congenital heart defect detection in general obstetric practice has been reported to be as low as 28%. Since the last decade, AI-based systems have been utilized in various fields of healthcare. Clinical diagnosis is widely acknowledged as an objective process based on the available facts and the specialist's expertise. The utilization of a computerized approach has been suggested as a significant factor in the analysis of physicians' interpretations. Therefore, machine learning and deep learning techniques are becoming more prevalent in the construction of CHD detection systems due to their capacity to effectively identify intricate correlations within extensive datasets.

5.1 *The machine learning approaches*

Machine learning that relies on human-created attributes is a semi-supervised learning approach whose primary phases are extracting and selecting attributes. Machine learning models have the capability to categorize various categories of CHD by taking into account their respective severity and location. Several research studies have demonstrated that machine learning models possess the capability to attain elevated levels of sensitivity and specificity when detecting CHD. Moreover, in certain scenarios, these models can surpass the diagnostic performance of human experts. Consistent and objective results provided by prenatal screening can potentially mitigate disparities and biases. The utilization of this method for the detection of coronary heart disease shows potential as a valuable resource that can improve prenatal healthcare and lead to a reduction in mortality rates. Comart and colleagues conducted a comparative analysis of multiple machine-learning methodologies for the categorization of fetal cardiac signals. A range of feasible AI models was utilized to analyze fetal heart rate signal specimens produced by SisPorto 2.0. The SVM and random forest models achieved accuracies of 99.21% and 99.07%, respectively [48]. Zhang and colleagues effectively conducted screening of the 2-D ultrasound standard plane through the utilization of a cascaded AdaBoost classification algorithm and local context data. Additionally, they introduced the notion of smart ultrasound scanning [54]. The researchers Christopher et al. employed the random forest regression technique to forecast the transparency, location, and orientation of ultrasound scans of the heart of the fetus. This was done with the aim of identifying the heart's phase from each video frame [55]. The results obtained were comparable to those of experts in the field. Shah et al. have proposed a model indicating the efficacy of multiple linear regression in the estimation of coronary heart disease risk. The study is founded on the acquisition of 2,000 cases of unprocessed information, each containing 20 distinct attributes that had been formerly developed [56]. The decision tree is considered one of the most extensively employed techniques in the field of data mining. The J4.8 decision tree has been predominantly utilized in a large number of investigations, owing to its reliance on binary distinction and efficiency gain. Alternative decision tree methodologies that have demonstrated efficacy include the Gini index and gain ratio. However, these techniques are not frequently employed in the context of heart disease detection. The authors Liu et al. proposed designing a predictive model for embryonic growth by utilizing machine learning techniques that rely on historical event data. The researchers analyzed the importance of identical features in in-progress pregnancy specimens and early loss of pregnancy specimens. The researchers employed fetal heart rate samples in conjunction with other physiological signals. Out of the six machine learning models, the random forest model achieved an F1-score of 97% [50]. The dataset utilized by Le et al. featured a congenital cardiac disease percentage of 14.1% within the investigated group. The study employed the random forest method to train a machine learning (ML) model for the purpose of evaluating the occurrence or nonexistence of congenital heart defects [49].

5.2 *The deep learning approaches*

The utilization of artificial neural network (ANN) data mining technique was employed for the purpose of identifying cardiac ailments. Due to the increasing cost of diagnostic procedures, there was a demand for innovative procedures that could predict cardiac issues in an inexpensive and readily available manner [57]. The authors, Paul et al., have presented a fuzzy decision support system that utilizes a genetic algorithm for the purpose of forecasting the risk stage associated with cardiac disease. The authors employed a genetic algorithm to develop a disease identification model by generating weighted fuzzy rules based on chosen features [58]. The study conducted by Wu et al. employed Mobilenet-based Fast-RCNN to forecast CHD using ultrasound scans. This approach has the potential to assist sonographers in acquiring fetal ultrasound scans during clinical procedures while also establishing a dependable foundation for subsequent fetal image analysis, thereby optimizing time management and improving overall efficiency. The study aimed to develop an automated method for identifying the typical segment of the fetal heart. The proposed model succeeded in achieving an accuracy of 90% [59]. Karimi-Bidhendi and colleagues proposed a novel approach utilizing a generative adversarial network (GAN) to artificially enhance the training dataset by producing synthetic cardiac magnetic resonance (CMR) pictures and associated room divisions. The FCN model was applied to the congenital CMR dataset, resulting in a mean Dice metric of 91.0% and 84.7% for the left and right ventricles at end-diastole, accordingly [60]. Various DL method for CHD detection is shown in Table 3.

Table 3. Segmentation techniques for chd detection

Authors	Ref.	Data	CHD Detection Method	Outcome
Comart et al.	[48]	2,126 fetal heart rate samples	SVM, Random Forest	Accuracy of 99.21% and 99.07%
Le et al.	[49]	3,910 singleton fetuses	Random forest	Sensitivity 93%, specificity 72%.
Liu et al.	[50]	Fetal heart rate samples	Random forest	F1-score 97%
Truong et al.	[51]	3,910 singleton fetuses	Random forest + nested cross-validation	Sensitivity 85%, specificity 88%
Hussain et al.	[52]	Physionet databases	SVM Gaussian	Sensitivity 93.06%
Selvan et al.	[53]	Coronary heart database	Naïve Bayes	Accuracy 98%
Wu et al.	[59]	1,839 Ultrasound frames	Mobilenet-based Fast-RCNN	Accuracy 90%
Karimi-Bidhendi et al.	[60]	CMR dataset	FCN	The average Dice metric is 91.0% and 84.7% for the left and right ventricles at end-diastole, respectively
Philip et al.	[61]	4D Ultrasound data	CNN	Dice score 0.78
Wang et al.	[62]	1,308 image data	Multi-channel CNN	Accuracy 93.9%
Pu et al.	[63]	Ultrasound video frame	Transfer learning	Accuracy 94.84%
Qiao et al.	[64]	Four-chamber view dataset	Residual learning	Accuracy 93%
Arnaout et al.	[65]	107,823 image frames	Ensemble of neural networks	95% sensitivity, 96% specificity
Lei et al.	[66]	PhysioBank dataset	UNet++ model with Squeeze-and-Excitation (SE) residual blocks	Accuracy 88.79%
Shozu et al.	[45]	Fetal ultrasound videos	DeepLabv 3+	Intersection over union 0.47
Nurmaini et al.	[39]	Ultrasound images	ResNet 50	Avg. accuracy 96.44%

The authors, Wang et al., suggested an automated approach for the analysis of multi-view echocardiograms utilizing a multi-channel CNN system based on depth-wise separable convolution [62]. Arnaout et al. utilized a dataset of 107,823 images obtained from 1,326 echocardiography tests and investigations of fetuses between 18-24 weeks of gestation. They employed an ensemble of neural networks to classify suggested cardiac views and differentiate between typical cardiac conditions and complex congenital heart disease. Ultimately, localization models were employed to compute conventional fetal cardiothoracic measures. The study involved a test set of 4,108 fetal surveys, wherein the model exhibited a high level of performance with an AUC of 0.99, 95% sensitivity, and 96% specificity in accurately distinguishing between normal and abnormal hearts. The sensitivity exhibited a level of comparability with that of real-time data and persisted in its robustness on images of lower quality and those originating from external sources [65]. The researchers Edupuganti et al. employed the Convolutional Neural Network architecture known as LeNet-10 to identify potential cardiac abnormality through ultrasound imaging. The objective of the study was to identify the impacted region and the site of any anomalies. The model under consideration achieved a precision rate of 98.37% and a sensitivity rate of 97.81% [67]. Arnaout et al. utilized an ensemble of neural networks to discern suggested cardiac views and differentiate between typical cardiac structures and intricate congenital heart disease. The experimental study utilized a total of 107,823 images obtained from 1,326 echocardiograms and ultrasound scans. The study attained a sensitivity rate of 95% and a specificity rate of 96%. The findings of this study suggest that the implementation of ensemble learning models could lead to a noteworthy enhancement in the identification of fetal congenital heart disease, provided that prescribed imaging guidelines are followed [68]. Table I shows several CHD detection methods and relevant details. Approach by computer vision techniques: In recent years, computer vision techniques have made significant advancements in the detection of CHD, particularly with the help of deep learning models applied to medical imaging [63–68]. Various studies have developed deep learning-based models to automate the analysis of echocardiographic images [69]. These models leverage CNNs for segmenting standard heart views, such as the four-chamber and left/right ventricular outflow tract (LVOT/RVOT) views, which are crucial for identifying structural anomalies in the fetal heart [70]. For instance, one model achieved an impressive 98.30% accuracy in detecting heart defects by training on fetal heart images using an instance segmentation approach [71]. In another approach, fusion features combining Mel-frequency spectral coefficients (MFSC) and other heart sound features were used to develop an assistive diagnostic system. This system leverages locally concatenated fusion and CNN models to automatically classify CHD from heart sound data, achieving accuracies of up to 94.79%. Such methods enhance the reliability of CHD screening in remote and underserved areas [72]. Recent advancements include improving the standard echocardiography views used for pediatric CHD diagnosis by adding new perspectives, such as the subxiphoid biatrial view [73]. This helps in capturing more comprehensive heart anatomy details, increasing the diagnostic accuracy for complex CHDs like coarctation of the aorta [74, 75].

6. Challenges and future directions

6.1 *Challenges*

The utilization of AI presents an intriguing opportunity for enhancing the early identification and treatment of CHD, a prevalent and severe defect in newborns. Nonetheless, the implementation of AI-based prenatal cardiac disease recognition encounters various obstacles and constraints that require resolution before its widespread integration into medical procedures. Several constraints exist, including:

The efficacy of AI algorithms is contingent upon the quality and quantity of data, as they require extensive and varied datasets to acquire proficiency and execute with precision. The acquisition of fetal echocardiography images and annotations of superior quality poses a challenge, owing to various factors such as fetal mobility, maternal adiposity, gestational age, and operator proficiency. Additionally, certain types of congenital heart disease (CHD) may have limited prevalence and could be inadequately represented in the existing data, resulting in potential biases and overfitting.

The utilization of AI-based prenatal cardiac disease recognition raises legal and ethical questions due to the delicate and private nature of the data involved, necessitating meticulous managing and safeguarding. The utilization of AI to guide parental decision-making raises ethical and legal considerations, particularly with regard to determining whether to proceed with or terminate the pregnancy or undertake fetal interventions. The aforementioned concerns necessitate unambiguous protocols and standards to safeguard patients and their relatives' well-being, confidentiality, and self-determination.

Medical incorporation and testing are necessary to widely adopt AI-based prenatal CHD screening into established perinatal care practices. Effective cooperation and interaction among diverse stakeholders, including medical professionals, heart specialists, radiologists, genetic counsellors, and bioinformaticians, is imperative. Moreover, it is imperative to verify machine learning algorithms through future investigations that employ real-world information and results to establish their therapeutic value and efficacy.

6.2 *Future direction*

There are various steps to take to implement AI in the field of prenatal heart disease detection. Some of them are discussed below.

- The integration of eHealth into medical facilities involves the provision of an assortment of amenities and frameworks. These consist of medical data derived from electronic health records (EHRs), unified data networks, and disease databases in conjunction with nonclinical frameworks.
- The process of digitizing EHRs produced by hospitals and clinics and subsequently transferring them to nationwide servers with suitable backup measures. The data produced may have practical applications in the realm of AI-based risk estimation and the identification of ailments, including CHD.
- The enhancement of testing services within healthcare institutions to cover diverse types of tests as a medical care component can enhance diagnostic capabilities for CHD and elevate familial risk estimation.
- Preparation of doctors and other medical professionals to utilize an EHR with an AI health system.
- Developing a cohesive system can help implement integrated CHD studies, AI, and policies into the medical milieu in healthcare organizations.
- Countrywide use of artificial intelligence and medical bioinformatics for interpreting echocardiograms, electrocardiograms, and ultrasounds should be considered to improve cardiovascular medical treatment and supervision.

7. Conclusion

The present study provides a comprehensive overview of the recent advancements and challenges encountered in applying artificial intelligence techniques, such as deep learning and computer vision, to detect congenital heart disease. Furthermore, we investigated prospective pathways for enhancing and investigating AI-based prenatal cardiac ailment detection. The distinctive advantage of artificial intelligence models lies in their remarkable capacity to acquire knowledge from data through repeated exposure. The utilization of AI has become a viable means of expediting and enhancing investigations and clinical trials pertaining to CHD. This is primarily attributable to the growing abundance and intricacy of available data and the emergence of heightened computing capabilities. Clinical practitioners and their patients may imminently reap the advantages of clinical decision-support mechanisms that aid in the customization of patients' medical evaluations and therapies and furnish instantaneous data on individual wellness metrics. Despite the obstacles that may arise during the integration of AI in the context of CHD, there are various prospects available for healthcare providers to investigate in numerous domains of CHD. The advent of advanced AI algorithms that can effectively process large datasets has opened up numerous research prospects for investigating and analyzing CHD throughout an individual's lifespan. These opportunities include collaborative efforts to construct predictive models for future occurrences of CHD and develop pharmaceutical interventions for patients with the condition.

Conflict of interest

The authors declare no competing financial interest.

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