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A review on identification of atrial septal defect using deep learning

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Abstract: The third most prevalent kind of congenital cardiac disease is atrial septal defects (ASD). Even with extensive shunts, the majority of individuals remain asymptomatic throughout their infancy. Echocardiogram, Chest X-ray, Electrocardiogram (ECG), Cardiac catheterization, MRI, and CT scan may all be used to detect the abnormality. Deep learning can be employed for automated estimation of the defect from the test result. The goal of this review paper is first to provide an insight into ASD, the methods for diagnosis, the application of deep learning models for distinguishing the defect, defect detection accuracy and algorithm parameters.

Keywords— Atrial Septal defect; Deep learning; Diagonostic tools; CNN; U-Net architecture;LSTM; Image Segmentation

1. Introduction

Congenital heart disease is the most often occurring congenital ailment, accounting for 28% of all congenital birth abnormalities (CHD). In medium-income nations, like as India, the care accessible for children with CHD is drastically different from that offered in high-income countries. Due to India's enormous population and insufficient resources, many children with CHD go undetected and mistreated. Over the previous three decades, India has made great progress in the care of children with CHD, but it is still woefully insufficient. To enhance the overall prognosis for children with CHD, interactions with doctors and other front-line health workers are required. Advocacy with health policymakers is critical to ensuring that greater resources are dedicated to the care of children with CHD at all levels of education [1]. A set of major cardiac problems that are present from birth is referred to as critical congenital heart disease (CCHD). The Atrial Septal Defect (ASD) is a defect in the atrial septum that allows blood to shunt between the two atria. It's one of the most prevalent congenital heart abnormalities [2], accounting for up to 10% of all congenital cardiac malformations and, together with the bicuspid aortic valve, the most often identified congenital heart defect in adults. The majority of children with ASD are detected by a pediatrician's unintentional observation of a heart murmur [3].

Artificial Intellect (AI) [4] is a wide term that refers to any computer programme (algorithms and models) that is designed to emulate human reasoning and intelligence. Deep learning (also known as deep structured learning) is a subset of artificial neural network-based machine learning algorithms. A computer model learns to do categorization tasks directly from pictures, text, or sound in deep learning [4]. Models are trained utilising a huge quantity of labelled data and multilayer neural network topologies. The development of an effective deep learning model for the detection of ASD might be highly beneficial to patients and sonographers. Here, a computer model is created to do image-based identification tasks. This paper's contribution is to analyse the deep learning algorithms used for recognising ASD, which is motivated by this concern. The objective is to first give an understanding of ASD, as well as identification techniques and the use of deep learning models to detect the issue.

2. Atrial Septal Defect

The typical human heart is a muscular organ that receives and pumps blood effectively. Because the body's tissues depend on the blood to provide sustenance (oxygen, glucose) and eliminate waste products, proper blood flow is critical to health (carbon dioxide). The cardiovascular system (heart, blood vessels) has two different circulatory systems under normal conditions: venous (right) and arterial (left)[5]. There are four chambers in the heart's interior: the atria, which hold blood, and the ventricles, which pump it out. The right ventricle transports the body's deoxygenated blood to the lungs through the right atrium. [1] Oxygenated blood from the lungs is circulated throughout the body via the left ventricle[2]. Four valves in the heart keep blood flowing in just one direction. Fetal lungs do not function as well as adult lungs do when it comes to oxygenating the blood. The placenta provides oxygen to the developing foetus within the mother's womb. The right atrium of the foetus is filled with oxygenated and deoxygenated blood. It contains three different structures that allow blood shunting from the right to left side of the heart[5] since the lungs require very little of this blood. Fetal lungs do not function as well as adult lungs do when it comes to oxygenating the blood. The placenta provides the foetus with oxygen. In the foetus, oxygenated and deoxygenated blood mix and settle in the right atrium, unlike in adults. These structures allow the foetus' heart to switch its flow from its right side over to its left[5] since the lungs need so little of this blood. The septum primum ("first partition"), a wedge of tissue that extends inferiorly, is formed as the apex of the atrium depresses between 3 and 4 weeks of foetal development. A foramen called ostium primum ("first mouth/opening") forms along the free side of the crescent-shaped septum, which divides the right and left atriums during the fifth week. By the end of the sixth week, the septum primum's growing edge reduces the ostium primum to nothing. To generate the second ostium, holes emerge in the first septum primum at the same time ("second opening"). Consequently, blood flow from right to left opens up before the old one closes. At the same time, the septum secundum (second partition), a crescent-shaped wedge of tissue, emerges from the atrium's ceiling. It's located close to the septum primum on the right side of the right atrium. Contrary to the septum primum, the septum secundum grows posteriorly and is thick and muscular. Right atrium floor to the foramen ovale at the inferior section of the foramen ovale. As the foetus grows, blood flows from the right to the left atrium through the aortic artery; this occurs throughout much of the development of the heart. This shunt closes during delivery due to the abrupt dilation of the pulmonary vasculature and the absence of flow via the umbilical vein. An atrial septal defect occurs when the septum secundum is insufficiently short to fully cover the ostium secundum after the septum primum and septum secundum are forced together at birth, allowing left-to-right atrial flow. The third most prevalent kind of congenital cardiac disease is atrial septal defects (ASD). Even with massive shunts, the majority of individuals remain asymptomatic throughout their childhood[3]. Figure 1 depicts the many morphological kinds of ASD [6] depending mostly on their location:

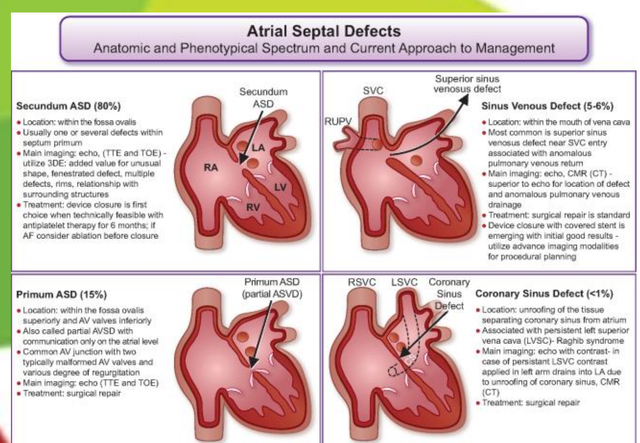

Figure 1: The different morphological types of ASD [1]

3. Methods for identification of ASD

3.1 Cardiac Murmur

The majority of children with ASD are discovered as a result of a pediatrician's unintentional identification of a heart murmur. Failure to thrive, feeding problems, dyspnea, or repeated lower respiratory infections are all possible symptoms of a newborn with ASD[3]. The characteristic auscultatory findings in big ASD include a normal first heart sound and a broad and fixed second sound. The natural split of the second sound is normally well heard in healthy young children, but it might be accentuated and persistent in the recumbent posture, leading to suspicion of an ASD.

3 3.2 Chest X-Ray

X-ray radiography is one of the most widely used procedures for detecting and diagnosing a wide range of disorders. In hospital archives all across the globe, a vast number of radiography pictures and reports are accessible. Chest enlargement of the right heart chambers In ASD, an X-ray may detect a hemodynamically substantial shunt [3].

3.3 Electrocardiography (ECG)

The electrocardiogram (ECG) is a transthoracic interpretation of the heart's electrical activity over time[7]. ASD is characterised by the absence of sinus arrhythmia. While partial right bundle branch block is a typical finding in ASD, the QRS tends to get longer as right ventricular volume overload increases. The patient's right atrial enlargement is commonly suggested by mild peaking of 'p' waves with little amplitude rise. The presence of substantial pulmonary hypertension and, in certain cases, pulmonary vascular disease is indicated by right axis deviation of the QRS [8]. The relevance of electrocardiographic evidence in the diagnosis of atrial septal defect is shown by Nermin Bayar et al. [9].

3.4 Echocardiography

An echocardiogram (often known as a "echo") is a picture of the heart in motion. With the use of high-frequency sound waves emanating from a hand-held wand placed on your chest, a sonographer may take pictures of the heart's valves and chambers and determine how well it pumps. Doppler ultrasonography and colour Doppler are often used in conjunction with echo to evaluate blood flow through the heart's valves [10]. The major method for the diagnosis and characterization of ASD is transthoracic echocardiography. The size, form, and position of the ASD, as well as its connection to neighbouring cardiac structures, should be delineated using several images [9]. The preferred imaging modalities include transesophageal echocardiography (TEE) and/or intracardiac echocardiography [11]. The usefulness of transthoracic (TTE) and transesophageal (TOE) echocardiography in the evaluation of different forms of atrial septal defect in adults was compared by Itzhak Kronzon et al [12]. TTE is the first-line imaging modality for the majority of adult patients with ASD, enabling reliable diagnosis, shunt measurement, and evaluation of haemodynamic implications, including pulmonary hypertension [6]. TOE is necessary for the correct assessment of defect size and shape before to or during transcatheter or surgical closure of ASD.

3.5 Cardiac Catheterization

It's a treatment that involves inserting a thin, flexible tube (catheter) into a blood artery and guiding it to the heart to diagnose or treat certain heart diseases. While invasive catheterization is not necessary for the diagnosis of ASD, it is the gold standard for shunt estimate [13]. Magnetic resonance imaging (MRI) 3.6 (MRI) Magnetic resonance imaging (MRI) is a medical imaging technology that creates detailed pictures of organs and tissues using a magnetic field and computer-generated radio waves [14]. Computerized tomography (CT) 3.7 (CT) A CT scan combines a sequence of X-ray pictures collected from various angles throughout your body with computer processing to generate cross-sectional images (slices) of your bones, blood arteries, and soft tissues. CT scan pictures include more information than standard X-rays [14].

4. Deep learning for the recognition of ASD

In the past 20 years, mortality from congenital heart disease (CHD) has decreased by half in high-income countries (HICs), whereas disability and death have increased in low- and middle-income countries (LMICs). Increasing surgical treatment in these nations may cut fatalities from congenital heart disease by 58 percent. However, identifying patients as soon as possible is critical to achieving better results. Neural networks and other machine learning models have the ability to properly identify congenital heart disease without the need of skilled individuals. A key issue is the variety of the diagnostic modalities utilised to train these models, as well as the CHD diagnoses included in the research. [15]. Hoodbhoy et al. [16] created an intelligent predictive system for the prediction and detection of cardiac disease based on modern machine learning methods. Heart disease may be prevented with accurate prognosis, but it can also be deadly if the forecast is erroneous. Bharti et al.[17] examine the findings and analyses of the UCI Machine Learning Heart Disease dataset using various machine learning methods and deep learning. 94.2 percent accuracy was achieved using a deep learning method. The intelligent detection of juvenile murmurs related to congenital heart disease (CHD) is shown by Jiaming Wang et al. [18]. To find the first and second heart sounds from a phonocardiogram (PCG) signal, a segmentation approach based on the discrete wavelet transform [19] paired with the Hadamard product was applied. Heart murmur diagnostic accuracy, sensitivity, and specificity were 93 percent, 93.5 percent, and 91.7 percent, respectively. Finally, an intelligent diagnostic approach for paediatric CHD murmurs has been successfully established and may be utilised for online CHD screening in children. If a nonprofessional volunteer captures PCG signal using an electronic stethoscope in any other posture, the procedure may not perform properly. Medical image segmentation tries to make changes in anatomical or diseased features in pictures more visible; it is often used in computer-assisted diagnosis. With the advancement and widespread availability of medical imaging equipment, X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound have emerged as four important image-assisted methods for clinicians to diagnose diseases, assess prognosis, and plan operations in medical facilities. It is required to segment certain critical items in medical pictures and extract characteristics from segmented regions to assist physicians in making correct diagnoses [4].

Convolutional neural networks (CNN) enable hierarchical feature representation of pictures in deep learning.

Because CNNs used for feature learning are unaffected by picture noise, blur, contrast, and other factors, they provide outstanding medical segmentation results. Because medical picture segmentation tasks often need high precision images, supervised learning is the most favored method [4]. The U-Net, introduced by Ranneberger et al. [20], was the first high-impact encoder-decoder structure, and it has been extensively utilized for medical picture segmentation. The heart's magnetic resonance imaging (MRI) provides for both planar and volumetric evaluations of cardiac architecture, which may aid in the identification of an atrial septal defect (ASDs). Yu Lu et al. [21] employed a variant of the U-Net architecture, which is widely used in deep learning, to separate the right atrium in MRI images from ASD patients. Segmentation accuracy is improved by using the proposed method. There is a major problem with existing encoder–decoder networks since the skip connection and encoder–decoder link can't retain both details and semantic information simultaneously. Remaining and dense connections, as well as high resolution semantic data obtained by deep monitoring, may all be investigated. Because atrial septal defects produce a slight heart murmur, it can only be heard by chance. Although an ECG may aid in diagnosis, it is difficult to detect specific problems. Hiroki Mori et al. exhibited enhanced diagnosis accuracy for Atrial Septal Defect by combining electrocardiograms [23] with a suggested deep learning model that included a convolutional neural network (CNN) and long short-term memory (LSTM) [22]. They made use of We employed a CNN and LTSMs-based deep learning model [24]. The accuracy, sensitivity, specificity, positive predictive value, and F1 score of the deep learning model were 0.89, 0.76, 0.96, 0.88, and 0.81, respectively. Two major restrictions were found when constructing the model. For starters, the amount of photos utilised for deep learning (DL) was rather tiny. The priming effect and the Hawthorne effect should be taken into account in the doctors' tests [25] [26]; each physician was instructed to determine whether the ECG was ASD or normal. This might have resulted in greater false positive and true positive ratios than if ASD had not been recognised as a possible condition. More accurate assessments may be feasible since the DL model can make a decision without being affected by such inputs. As a result, if these constraints are addressed in future research, the diagnostic quality of the proposed deep learning ECG approach might be significantly improved for clinical pre-examination ECG screening applications. Echocardiography, which uses ultrasound technology to capture high-resolution images of the heart and its surrounding tissues, is the most often used imaging modality in cardiovascular medicine. Deep learning interpretation of echocardiograms was achieved using convolutional neural networks by Amirata Ghorbani et al. [27]. A deep learning algorithm used to echocardiography may identify local cardiac structures, measure heart function, and predict systemic phenotypes that impact cardiovascular risk but are difficult to detect using human interpretations. When it came to detecting pacemaker leads as well as left atrial and cardiac hypertrophy and end-systolic and diastolic volumes and ejection fraction, EchoNet, their deep learning network, got it right every time. This investigation shows that EchoNet pays attention to critical cardiac structures and places a high priority on hypothesis-generating regions of interest while making predictions about complex symptoms. It's critical to test for septal abnormalities accurately to help radiologists understand their findings. Deep learning was suggested by Siti Nurmaini et al. for the accurate identification of septal abnormalities in prenatal ultrasound pictures [28]. Multiple objects, such as the atria, ventricles, valves, and aorta, may be found in the embryonic heart. Furthermore, substantial variances might be caused by fuzzy borders (shadows) or a lack of uniformity in the acquisition procedure. Mask-

RCNN (MRCNN) [29] is used in this work to handle foetal ultrasound pictures and to identify and segment abnormalities in heart walls with numerous objects. For multiclass heart chamber identification, the proposed MRCNN model performs well with 97.59 percent accuracy in the right atrium, 99.67 percent accuracy in the left, 86.17% accuracy in the left ventricle, 98.83 percent accuracy in the right ventricle, and 99.97 percent accuracy in detecting heartbeats in the aorta, among other values. The proposed method provides for the reliable identification of septal anomalies in either the atria or the ventricles. In order to ensure the accuracy of the hole detection, experts have checked all of the data. The septal defect dataset has a well-known problem: it is a very small and exacting dataset. Transthoracic echocardiography (TTE) is the primary imaging tool for individuals with congenital heart disease. Transthoracic echocardiographic images of patients with congenital heart disease (CHD) may be improved by using acoustic shadowing removal techniques developed by Gerhard-Paul Diller et al. [31]. There were comparisons made between DL algorithms trained on CHD samples and those trained on normal cardiac samples. Deep neural network-based autoencoders [32] were developed to denoise and eliminate acoustic shadowing aberrations based on typical echocardiographic apical 4-chamber pictures, and performance was assessed by visual inspection and by calculating cross entropy. People with congenital heart disease and those with normal hearts may benefit from the use of autoencoders to reduce noise and eliminate artefacts, according to a new study. Models trained just on structurally normal cardiac samples work well in CHD, however the data show the necessity for specialized image augmentation systems trained specifically on CHD samples.

5. Conclusion

Deep learning has shown a lot of promise in terms of detecting ASD. Deep learning-based algorithms have been found to be effective in defect identification throughout the preprocessing, feature extraction, feature selection, classification, and clustering processes. In terms of fault identification accuracy and algorithm parameters, the performance of several diagnostic approaches was discussed. In conclusion, we may infer that an effective deep learning model for the detection of ASD might be immensely beneficial to patients and sonographers.

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