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Review

A Review on the Use of Artificial Intelligence Algorithms for the Prediction of Fetal Brain and Heart Abnormalities

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ABSTRACT

Artificial intelligence is an essential tool in the fight against congenital foetal anomalies in the field of foetal medicine. With the use of ML algorithms and CNNs, abnormalities of the heart and brain in fetal magnetic resonance imaging (MRI) and ultrasonography may be identified, detected, and localized. Prenatal abnormalities may be better identified and predicted with the use of Artificial Intelligence (AI) systems that can do complex assessments of abnormal picture patterns. This narrative review delves into the use of AI in congenital anomaly detection and risk stratification. Machine learning and deep learning algorithms have the potential to enhance fetal imaging (ultrasonography and MRI) exams in order to shorten examination times, lessen the burden on the clinician, and improve the accuracy of diagnoses for fetal abnormalities. The purpose of this research is to assess the efficacy of the algorithms already in use to automate the detection of abnormalities in the developing brain and heart of pregnant women. The article also contrasts ML and DL algorithms by looking at how well they identify abnormalities in the developing foetus's brain and heart. For the purpose of congenital anomaly prediction, the study stresses the need for bigger and more diverse datasets, analysis of longitudinal data, and integration of several data sources. Additional emphasis is placed on the value of interpretability, human clinical experience, and prospective validation in actual clinical contexts.

Keywords
Deep learning; Machine learning; Artificial intelligence; Congenital heart disease; Fetal anomaly.

INTRODUCTION

An anomaly is something that doesn't fit the pattern or the expected. Fetal anomalies are defined as conditions that are abnormal or unanticipated in the development of the baby during pregnancy [1,2]. Fetal abnormalities are sometimes known as birth defects or congenital anomalies [1-3]. The organs and systems of a growing fetus, such as its heart, lungs, kidneys, and limbs, structural abnormalities affecting the face, heart, and lungs may cause illnesses such as spina bifida, cleft lip, congenital abnormalities of the brain and heart, and missing toes [1]. A functional abnormality is a disruption in the normal functioning of a bodily system or component, such as the central nervous system (CNS), sensory perception, or the brain [4]. Conditions including Down syndrome, muscular dystrophy, developmental impairments, seizures, and blindness are all examples of functional birth abnormalities [5].

Birth defects affecting the heart's structure are known as fetal heart disorders [6]. The growing baby inside the uterus exhibits several abnormalities throughout pregnancy. About half a million American individuals have congenital cardiac disease, according to the World Health Organization [6]. One in one hundred infants are born with a congenital heart defect as a consequence of a genetic or chromosomal abnormality, such as Down syndrome. Fetal heart disease is more likely in infants whose mothers drink excessively or use medications while pregnant, as well as in those whose mothers get a virus in the first trimester of their pregnancies or who have a family history of congenital heart defects [7].

Problems with development at any point in the embryonic or foetal phases may also lead to birth defects called congenital brain malformations [8]. Possible symptoms include hypotonia, seizures, or developmental delay in the nonspecific clinical presentation. The advent of more sophisticated imaging techniques has allowed for the development of more precise and timely treatment plans [9]. Prenatal treatment often includes ultrasound screenings for foetal abnormalities between the 18th and 23rd week of pregnancy [10]. Babies' heads, brains, and facial features, as well as their limbs, hands, and feet, are all areas that the anomaly scan aims to detect. Despite this, fetal MRI has been more used in clinical settings for detecting fetal brain disorders in the last decade [11].

Furthermore, AI is playing an important role in fetal medicine to prevent congenital fetal malformations. Artificial Intelligence (AI) refers to a computer's capacity to learn, reason, and interact in ways that are typical of intelligent humans [12,13]. Deep Learning (DL) and Machine Learning (ML) are two branches of artificial intelligence [14,15]. Convolutional Neural Networks (CNNs) are a prominent kind of deep learning algorithm; new research has shown that CNNs can perform image recognition tasks quite well [16,17]. In foetal ultrasonography and magnetic resonance imaging (MRI), ML algorithms and convolutional neural networks (CNNs) have shown the capacity to identify [18], locate [19], and detect [20] standard planes. While artificial intelligence (AI) has been increasingly used in fetal imaging, the majority of these studies have focused on identifying normal fetal structures rather than developing AI algorithms that could conduct detailed analyses of abnormal patterns in fetus images to classify and predict congenital malformations [21–23].
Finding prenatal brain abnormalities using ML and DL algorithms to examine massive datasets is the focus of this research. disorders affecting the heart. Early treatments and preventative actions may be made feasible by predicting the start and duration of prenatal anomalies, such as congenital brain and heart defects. However, many publications have reviewed research on the use of AI algorithms for fetal heart and brain study [24–29]. The prediction of cardiac and brain disorders utilizing automated diagnosis based on ultrasound and MRI has not been previously covered in a state-of-the-art study. This review compiles research that has used ML and DL algorithms to forecast embryonic cardiac and brain abnormalities. The following research issues are addressed in this review, which is a contribution to foetal healthcare:

RQ1: Which imaging techniques are being utilized for fetal anomaly detection of brain and heart?
RQ2: How well does Artificial Intelligence (AI) detect both nor- mal and abnormal features of the most common congenital defects affecting the fetal CNS and cardiovascular system?
RQ3: Which algorithms are most commonly utilized for the prediction of fetal brain and heart anomalies?
RQ4: What are the current applications of AI-based detection systems in diagnosing abnormalities of fetal central nervous sys- tem and heart?

Methodology

Keeping the PRISMA criteria in mind, we searched the Google Scholar and Web of Science databases extensively for research publications. We used the following terms: deep learning, machine learning, congenital heart illness, ultrasound, fetal magnetic resonance imaging, congenital brain abnormality, congenital heart anomaly in the fetus, and artificial intelligence. From 2014 to 2024, we were only able to locate 95 articles.

For this review, we looked for English-language studies that discussed fetal scanning using MRI and ultrasound utilizing ML and DL algorithms. Two separate reviewers looked over each paper, using the title, abstract, and full text as criteria. Studies that met the following criteria were included in this evaluation to guarantee focused analysis: 1) published in English, 2) powered by artificial intelligence, 3) studying congenital abnormalities of the heart or brain, and 4) including all relevant information. As shown in Figure 1, fourteen papers were identified as having a high level of relevance to anomalies in the embryonic heart and brain after the exclusion criteria were applied.

a) Ultrasonography

Prenatal imaging diagnosis using ultrasound is a noninvasive, nonradiative, easy, and inexpensive method [30]. By seeing the baby and its appendages, prenatal ultrasonography provides a non-invasive way to evaluate fetal growth parameters, identify any congenital abnormalities, and assist with overall fetal diagnosis [31]. It may provide thorough information on foetal anatomy with improved diagnostic accuracy and high-quality images [32]. Currently, two-dimensional (2D) imaging and three-dimensional (3D) ultrasound are often used to evaluate fetal anatomy, diagnose diseases, and assess organ functioning [33]. The frequency of congenital disabilities may be effectively reduced when pregnant women get frequent ultrasonography tests. However, there are a number of roadblocks in the clinical pipeline that foetal ultrasonography is now attempting to overcome. The accuracy of the examination is affected by a multitude of circumstances, such as the rapid fetal motion, the thick abdominal wall of pregnant women, and inconsistent interpretations amongst clinicians [33].

Regardless of the gestational age, a prenatal ultrasound serves two essential functions: screening and diagnosis. In an attempt to enhance the diagnostic accuracy for foetal anomalies, screening and diagnosis based on Artificial Intelligence (AI) have been developed in the last 10 years [32,33]. The primary emphasis of these AI systems are
3 important domains: 1) the process of automatically recognizing human body parts,

2) taking standardised measures, and 3) identifying abnormalities in the ultrasound pictures. Due to the time-consuming nature of obstetric ultrasonography, the adoption of AI has the potential to streamline processes and reduce examination duration [33]. Despite the introduction of several machine learning and deep learning approaches to provide high resolution imaging and precise measurement for obstetric ultrasonography, much of the relevant research is still in its early phases [19,34].

b) MRI (Multi-Functional Imaging)

A safe substitute for X-rays for inspecting a developing fetus is fetal magnetic resonance imaging (MRI). There are currently no concerns about the method, which employs radio waves and magnets to generate intricate images [35]. It was in 1983 when magnetic resonance imaging (MRI) during pregnancy was first described [36]. The first obstetric applications were mostly due to maternal and pelvic abnormalities [36,37]. Fetal Magnetic Resonance Imaging (fMRI) [35] includes a comprehensive assessment of the placenta, umbilical cord, and amniotic sac. Accurate interpretation of foetal magnetic resonance imaging (FMRI) may provide valuable information for research, management choices, treatment planning, and prenatal counseling. Fetal brain development problems may be reliably diagnosed with the use of magnetic resonance imaging (MRI), which provides detailed images for precise assessment. More recent research on congenital cardiac abnormalities has also improved counseling for affected pregnancies [37]. The indications of fetal magnetic resonance imaging are briefly described in Table 1.

Several studies have shown that prenatal magnetic resonance imaging (MRI) complements and even outperforms fetal ultrasonography in terms of precisely depicting the body's anatomy [38]. The examination and identification of many prenatal anomalies may be accelerated by its increased usage [38]. Furthermore, MRI gets beyond some of the technical issues with ultrasonography, such as an irregular fetal position, insufficient amniotic fluid volume, and a high maternal body mass index [39]. Maternal habitus, fetal lying, and oligohydramnios may all degrade the quality of maternal ultrasound images. These issues are no longer an issue with MRI because to post-acquisition processing that allows motion correction to be performed to the brain and the abdominal cavity [35,36,40]. Using state-of-the-art MRI methods such as Diffusion-Weighted Imaging (DWI) and Magnetic Resonance Spectroscopy (MRS), researchers have examined fetal MRI [40]. Fetal brain diffusion imaging has potential uses in studying both degenerative and maturing brain states.
Accurate interpretation of foetal magnetic resonance imaging (MRI) requires radiologists and clinicians to have a knowledge of the normal developing foetal anatomy [35]. Age of the foetus, sometimes called gestational age, is an important factor to consider when depicting foetal anatomy [35]. The current state of fetal MRI analysis is not always optimal for accurate assessments because it requires looking at a large number of sequences and pictures. Also, there are holdups since there aren't enough experts. The use of AI may automate these processes, which improves the efficiency, consistency, and speed of fetal MRI analysis [41]. Using AI models in fetal MRI analysis is now under investigation. Key anatomical components and scan segmentation may be automatically detected by these models [42]. Numerous artificial intelligence models, most notably Res-Net and Convolutional Neural Networks, have work over the whole gestational period (17–38 weeks) [43–46]. A few of models achieved accuracy levels of 95% [47] or above. A.I. may be useful for picture reconstruction, as well as for preprocessing and postprocessing photos of foetuses [48]. Placenta identification, foetal brain segmentation, foetal brain extraction, prediction of congenital heart disease, and gestational age are all areas that might benefit from the use of artificial intelligence (AI) (Table 1).

b) Fetal Echocardiography

Fetal echocardiography is a specialized ultrasound exam that checks the developing baby's heart. To improve the accuracy of di- agnosis, fetal echocardiography combines both grayscale and color Doppler ultrasound [50]. Grayscale images show the structure of the heart, while color Doppler allows visualization of blood flow within the heart chambers and major vessels. It uses various ul- trasound views, including the upper abdomen, four-chamber view, five-chamber view, short axis view, three-vessel-trachea view, and longitudinal views of the aortic arch, ductal arch, and systemic veins [50,51].
Fetal echocardiography is an extremely specific and sensitive diagnostic procedure [50,52]. These days, fetal echocardiography is regarded as an essential part of the standard fetal anomaly scan. Most countries offer this type of scan in an effort to detect serious malformations, still, the detection rates of antenatal CHD are lower than those of the majority of other major structural anomalies [52]. Table 2 summarizes the use of ML and DL algorithms for analyzing fetal echocardiograms.

Fetal Abnormalities

a) Fetal Brain Anomalies

With a 1% incidence rate, anomalies of the CNS rank second among the most prevalent congenital fetal malformations [58]. The second-trimester anomaly scan uses special ultrasound techniques, like trans-ventricular and trans-cerebellar views, to examine the fe- tal skull. With the advancement of AI-assisted ultrasound diagno- sis, it was possible to identify fetal brain anomalies with 92.93% accuracy [28]; as a result, AI has been predicted to replace other screening techniques for fetal malformations of the central nervous system. Table 3 summarizes the studies done to predict fetal brain anomalies.

I Algorithms

Predicting abnormalities in the developing brain and heart makes heavy use of deep learning and machine learning methods. The study comes to a close with this section by discussing the most popular algorithms used for fetal analysis. With the help of Machine Learning (ML), computers may gradually get better at some activities without requiring constant, step-by-step human programming. Deep Learning (DL) is a subfield of machine learning that relies on neural networks structured into several layers, often ranging from four to hundreds. The process of picture categorization in computer vision

via the use of automated, layer-by-layer pattern recognition in photos. A computer can then "understand" the picture and draw conclusions from it. The interplay between artificial intelligence, machine learning, and deep learning is shown in Figure 2, which also showcases DL methods like convolutional and recurrent neural networks and ML approaches like logistic regression, random forests, and support vector machines. Based on the specific problem at hand, a plethora of different machine learning algorithms have been developed, each with its own set of pros and cons. While this review does not aim to provide a comprehensive description of these techniques, it does direct the reader to several excellent internet resources for learning more about them.

Machine learning approaches may be broadly categorized as either "supervised" or "unsupervised" learning. For supervised learning to be effective, labelled training data must be readily accessible. Applying what it has learned to fresh, unlabeled data, the algorithm is able to generate more precise predictions. Additional methods include unsupervised learning. Unsupervised learning differs from supervised learning in that it does not include labeling data but instead asks the computer to find patterns or groups within unlabeled data. Although the majority of medical AI research focuses on supervised learning, unsupervised learning has the potential to uncover hitherto unseen patterns in patient data.

Artificial neural networks are cutting edge when it comes to medical AI. Superhuman performance in some medical activities has been achieved via the construction of these models. Different kinds of neural networks have been developed to excel at certain jobs; for instance, convolutional networks are great at computer vision and recurrent networks are great at language processing. To evaluate pictures captured by foetal echocardiography, Convolutional Neural Networks (CNNs) have been used.

screen throughout the second trimester of pregnancy and phy. Fetuses between the ages of 18 and 24 weeks are the subject of this investigation. They found out that it may be distinguished between normal heart development and the existence of congenital heart defects [60,62]. In a neural network, each layer has a number of linked perceptrons, which are processing units. The first layer receives data, such a foetal echocardiography picture. The data is sent into the network in successive layers, with each layer building upon the one before it to extract ever-more-complex characteristics. The network is able to learn and generate predictions by using its tiered processing architecture.

The Steps Before and After Processing an Image With the help of motion-correction and pre-processing technologies, it is possible to get high-quality pictures of a moving object, which is a significant obstacle in foetal imaging. This used to need the frequent re-acquisition of sequences and adjustments to acquisition planes by a trained technician. This is quite labor-intensive and may vary greatly depending on the operator. Patients who are pregnant and resting still in a confined MRI machine may have trouble with extended scan durations. Better picture quality and maybe reduced scan durations may be the consequence of automatic fetal motion correction during startup.

A deep learning technique was detailed by S. Oldham et al. [63] that could automatically recognize foetal landmarks and predict foetal positions using 15 key points. This enabled the automatic reading of parameters, which might reduce the need for MRI scans and the amount of time technicians spend on them. When it came to predicting fetal posture, the researchers' model worked quite well. The average discrepancy between the anticipated and achieved poses was under 4.5 mm. The comparison between the model's output and actual fetal posture data allowed for this quick prediction (less than 1 second).

Using AI algorithms for image post-processing allows for consistent and time-efficient tissue segmentation. The developing brain of the foetus has recently been the subject of many studies. 3D models of the developing brain have traditionally relied on the manual delineation of 2D pictures. Segmentation of a diverse group of foetal brain pictures, including those with artifacts, was successfully documented by N Khalili et al. [64] using the U-net technique. Even normally assessed by hand, CNNs can reliably calculate biparietal (BPD) and trans-cerebellum diameters.

Metrics for Performance

While majority of the studies in this study employed the accuracy measure, a small number of them used AUC. Sensitivity was only evaluated in 61.3% of the trials. There was a paucity of information on accuracy in several studies that examined performance (38%). Although there was an emphasis on developing accurate prediction methods for foetal problems, no studies looked at their potential therapeutic use.

Time-Honored AI Use in Prenatal Imaging

This section of the article gives a high-level summary of the conventional methods now used for fetal analysis using several imaging modalities. The skill of the technician doing the ultrasound is crucial in determining the proper fetal position, also known as the fetal standard plane. Problems develop, nevertheless, due to the fact that ultrasound pictures may seem quite different from one pregnancy to another (poor inter-class similarity) and even from one ultrasound to another (high intra-class variability). Because of this, creating automated systems that use pre-programmed picture recognition becomes more challenging [65]. In this case, AI may be useful. Without the requirement for manually developed features, DCNNs may use their feature representation skills to discriminate across comparable ultrasonic images.

Additionally, AI algorithms are contributing to the intelligent measurement- expansion of the skull's diameter. Prenatal diagnosis of anomalies, evaluation of growth parameters, developmental progress, gestational age, and weight may all be informed by HC, making it an important biometric indicator [66,67]. The reliability of fetal HC measurements may be compromised by factors such as interobserver variability and partial border missing in cranial ultrasonography pictures. Another issue with ultrasound pictures is the lack of contrast and the presence of artifacts. This makes manual measurement of foetal HC a laborious and time-consuming process, even for highly experienced sonographers. Accurate and precise HC measurement is crucial in prenatal ultrasonography.

Abdominal circumference is the main measure used to calculate foetal weight [68], which is clinically important for evaluating foetal development and doing early screening for foetal abnormalities or growth limitation in the womb [69]. Raising the precision of the measurement may lessen the severity of these disorders' effects on the developing fetus. Finding the normal abdominal plane is something that sonographers must achieve by hand while working in clinical practice. Differences in foetal position, oligohydramnios, and the thickness of the abdominal wall during pregnancy might affect the precision of AC measurements [68,69].

We need a fast and accurate mechanism to measure AC so sonographers can do their jobs better. Clinical applications rely on accurate foetal abdomen segmentation from ultrasound pictures. Comparing CNN performance to other approaches, they do quite well in this job. It is also crucial to measure the Nuchal Translucency (NT), which is the accumulation of fluid at the back of the fetal neck [70]. Down syndrome and other newborn abnormalities, as well as unfavorable pregnancy outcomes, may be linked to increased NT thickness [70], [71,72]. Positioning the foetus in the typical sagittal plane allows for more precise measurements of NT thickness and allows for the early identification of structural anomalies and genetic disorders in the embryo. Still, getting accurate measurements of NT thickness and standard plane acquisition is no easy feat. Some of these challenges include ultrasound pictures with a poor signal-to-noise ratio, the fetus's movement in the early stages of gestation, and the short fetal posterior rump length. Crucial biometric activities take 25.56% less time for experts compared to untrained sonographers [72].

Combining AI with fetal brain ultrasound has many additional important applications, one of which is gestation age estimate. Ultrasound measurements of fetal landmarks provide a reliable way to estimate gestational age during early pregnancy. However, the inaccuracy in ultrasound-estimated gestational age (GA) grows with time when the diversity in fetal growth and development is disregarded; in some investigations, the error even surpasses two weeks [72,73]. In light of this, it is prudent to look into developing a reliable model for evaluating GA in the intermediate and final stages (Figure 3).

Discussion

Several articles on using ML and DL for fetal ultrasound and MRI evaluation are part of this study. Deep learning algorithms use a convolutional neural network (CNN) with many hidden layers to extract important characteristics from a limited set of training examples, allowing them to make high-performance predictions. The neural networks are designed to enhance prenatal imaging evaluation processes by automatically identifying the foetal heart and brain. By doing so, we can shorten the testing period while increasing the accuracy of the method. All of the methods reported in the studies that were examined achieved their aims of detecting fetal brain and heart abnormalities or associated biometric assessments with accuracy rates higher than 90% [74,75]. The findings show that the estimate of fetal parameters is becoming more accurate and automated. Congenital cardiac disorders account for the vast majority of congenital heart abnormalities [59]. We want to enhance the identification rates of congenital heart disorders with improved precision by incorporating ML and DL into ultrasound assessments. Scientific studies have shown that artificial intelligence systems can accurately detect embryonic features at any gestational age, even in the first trimester. By doing so, we may lay the groundwork for an intelligent clinical decision support system tailored to early-stage foetal echocardiography, which will be automated and built utilizing Deep Learning (DL) architectures.

Such algorithms have recently emerged, demonstrating the versatility of AI in foetal imaging. AI might revolutionize prenatal care by providing more accurate and efficient methods of detecting and diagnosing fetal problems. These improvements show how AI is changing the game in foetal analysis and bode well for foetal healthcare in the future. Anom-

Among the many types of congenital fetal abnormalities, central nervous system anomalies are the second most common [58]. An alternative screening method for central nervous system abnormalities in foetuses, AI-assisted ultrasound diagnosis has an accuracy rate of up to 99% in detecting fetal brain standard planes. In terms of detecting congenital brain abnormalities in fetuses, an impressive accuracy of more than 96% has been reached [74].

This approach emphasizes the efficacy of AI algorithms as helpful tools for inexperienced doctors to improve their diagnostic abilities. With the use of AI, sonographers can automatically detect the neck area in ultrasound pictures and estimate the nuchal translucency in instances with Down syndrome. We cover all the bases in our study, including several ML and DL algorithms, ongoing studies, pros and cons, potential obstacles, and anticipated applications in gynecology. This comprehensive research demonstrates that AI has significant potential for prenatal diagnosis, particularly in cases of congenital anomalies. Better patient outcomes could result from its use in foetal medicine by removing diagnostic roadblocks and increasing treatment possibilities.

Conclusion

Healthcare providers that depend on image-based data for diagnosis and decision-making might greatly benefit from deep learning (DL), a subfield of artificial intelligence, due to its capacity to identify patterns in photos. Thanks to its remarkable development over the last several years and its improved capacity to detect fetal brain and heart abnormalities during pregnancy, artificial intelligence is now being considered as a potential screening tool to supplement or replace traditional methods for fetal abnormality detection. Artificial intelligence (AI) can correctly recognize the anatomy of the brain and heart, according to scientific studies. Research has shown that convolutional neural networks (CNNs) in particular outperform professionals in prediction and similarity when tasked with differentiating between typical development and abnormalities of the heart or brain. Artificial intelligence has allowed for the very accurate automated assessment of fetal head biometry as well as the identification of brain areas and planes. During the process of detecting fetal brain abnormalities, there was a decrease in false-negative results and an improvement in anomaly detection compared to professional sonographers. More accurate and efficient methods of detecting and diagnosing fetal anomalies are one manner in which artificial intelligence (AI) can enhance prenatal care. These advancements show how AI is changing the game and bode well for the future of foetal healthcare.

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