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Advancements in Deep Learning Techniques for Enhanced Assessment of Fetal Anomalies in Prenatal Imaging: Review of Current Applications and Future Directions

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Abstract

Background: Deep learning (DL) has emerged as a transformative technology in the field of medical imaging, particularly in prenatal assessments. The application of DL algorithms in fetal imaging aims to address challenges such as human subjectivity and interobserver variability, while enhancing diagnostic accuracy.

Methods: This review synthesizes recent advancements in the application of deep learning techniques for evaluating fetal anomalies. A comprehensive literature search was conducted to gather evidence on the efficacy of DL in various aspects of prenatal imaging, including anatomical assessment, biometric measurements, and the detection of congenital abnormalities.

Results: The findings indicate that deep learning models exhibit superior performance in identifying normal and abnormal fetal anatomy compared to traditional methods. These models effectively classify images, localize anatomical structures, and segment key features, significantly reducing examination times and improving workflow. Furthermore, multiple studies demonstrate that DL can mitigate the impact of human error, achieving classifications that rival or exceed those of experienced sonographers.

Conclusion: The integration of deep learning into prenatal imaging holds considerable promise for enhancing diagnostic capabilities and improving patient outcomes. As these technologies evolve, they offer the potential to support clinicians, particularly in resource-limited settings where access to skilled sonographers is limited. Future research should focus on refining these models and ensuring their clinical applicability to maximize the benefits of deep learning in obstetric care.

Keywords: Deep Learning, Fetal Imaging, Prenatal Assessment, Congenital Anomalies, Ultrasound Technology

Introduction

Deep learning (DL) is regarded as the preeminent artificial intelligence (AI) instrument for image analysis overall [1,2]. Deep learning algorithms excel in picture identification and classification, making them helpful in medical imaging. Deep learning models have shown the capacity to equal or surpass human performance in tasks like image categorization, detection, and segmentation [3-5]. Consequently, deep learning has been suggested as a prospective auxiliary instrument for physicians in medical imaging. A recent assessment determined that more than 80% of published research on the use of AI in medical imaging employed a deep learning technique [1,2,6].

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In recent years, deep learning has garnered significant appeal in the domain of prenatal imaging, as seen by the substantial volume of published scientific research using this methodology [7-10]. In fetal imaging, deep learning (DL) is anticipated to mitigate issues associated with human analysis, such as subjectivity and interobserver variability, while also decreasing examination durations. Additionally, it may be used in the instruction of novice and unskilled physicians [11-13]. This State-of-the-Art Review offers a thorough examination of the use of deep learning in prenatal imaging. We elucidate the use of deep learning in prenatal imaging, emphasizing the evaluation of normal and abnormal fetal anatomy, biometric measures, and intrapartum ultrasonography.

Deep learning

'Artificial intelligence' refers to a computer's capacity to execute activities linked to human intellect, including learning, decision-making, visual perception, and voice recognition. Unlike human thinking, AI algorithms are proficient at detecting intricate patterns in data to provide an automated quantitative answer to a problem [1]. This indicates that their outcomes are more precise and repeatable than those of people. Machine learning algorithms, a subset of artificial intelligence, empower computers to learn and improve their performance via 'experience' (utilizing available data), without explicit programming. Numerous machine-learning techniques exist, with deep learning (DL) being the most significant in the domain of medical imaging (Figure 1) [2].

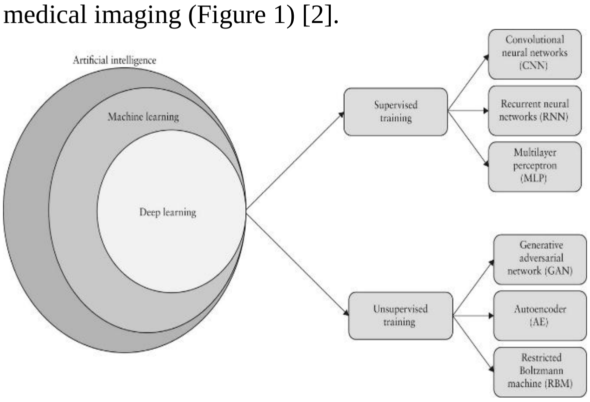

Figure 1. Summary of primary categories of deep learning algorithms categorized by training methodologies.

The architecture of deep learning models is complex and comprises several deep layers of artificial neural networks. Convolutional neural networks (CNN) are the most often used, however several other forms of deep neural networks exist (Figure 1). Deep learning models may examine extensive datasets in a layered, non-linear fashion, using pattern recognition to extract highly representative picture attributes for the purpose of labeling an image (e.g., as normal or abnormal). [14] Deep learning models may be constructed with either a supervised or unsupervised learning methodology. A supervised deep learning model, the most prevalent form, necessitates tagged or 'ground-truth' data as input for the neural networks during the training phase. The model's performance is then evaluated using unlabeled data, including normal brain scans and images exhibiting ventriculomegaly that have not been annotated by human operators, during the testing phase. Thereafter, the deep learning model will provide a forecast and categorize the picture. Conversely, unsupervised learning methods do not need labels. The deep learning model identifies primary patterns and similarities in the input data to categorize the photos in the output [15].

1. The Advantages of Utilizing Deep Learning In Fetal Imaging

Prenatal ultrasonography has significantly advanced over the years; nonetheless, the overall detection rates of congenital abnormalities continue to be low [16]. A primary reason for this is the human aspect. Navigating the ultrasound probe through intricate fetal anatomy to achieve the appropriate scanning plane, evaluating each fetal anatomical feature, and arriving at an accurate diagnosis requires years of training and comprehensive understanding of fetal anatomy [17-20]. Furthermore, issues intrinsic to ultrasonography, such as acoustic shadows, speckle noise, motion blurring, and indistinct boundaries, may potentially exacerbate the poor detection rates [21]. A further drawback of ultrasonography is the significant intra- and interobserver variability, particularly in biometric measures, which may lead to considerable inaccuracies in fetal weight estimate, leading in the misclassification of small- or large-for-gestational age fetuses [22].

2. The Mechanisms of Deep Learning In Fetal Imaging

The prospective applications of deep learning in obstetrics include the detection of normal and abnormal fetal anatomy as well as the assessment of fetal biometry. For these applications, deep learning models include one or a combination of up to four tasks: classification, localization, object identification, and segmentation, depending upon the required output. Classification designates a binary 'class label' to a picture, such as normal/abnormal or correct/incorrect anatomical orientation. Localization determines the exact position of an item inside an image, facilitating the identification of anatomical landmarks and enabling automated measurements. Object detection integrates classification and localization, simultaneously identifying the position of fetal structures in a picture (and, if required, their measurement) while categorizing them as normal or abnormal. Ultimately, segmentation refers to the identification of an item inside the picture. It resembles localization, however, also evaluates the morphology (form, volume, and contour) of the item, and may be integrated with classification tasks to categorize the picture as normal or aberrant [5].

This innovative technology has characteristics that may assist both novice and seasoned operators. The automated assessment of biometric parameters or identification of anatomical landmarks would assist the novice operator conducting a fetal screening scan, while deep learning models designed to detect fetal malformations could bolster the confidence of the junior examiner in diagnosis and notify a more seasoned operator of subtle anomalies that might otherwise be missed [23,24].

3. The Potential of Deep Learning to Enhance Fetal Imaging

Biometric measures are used to assess gestational age (GA) and track fetal development. To do this, many fetal components, including the fetal head, abdomen, femur, cerebellum, and crown–rump length (CRL) (before to 14 weeks of gestation), are assessed using conventional biometry planes [25-27]. The measurements are labor-intensive and dependent on the operator, necessitating accurate capture of the standard plane prior to the manual positioning of the calipers. Complete automation using deep learning may mitigate interobserver variability and decrease examination durations, hence enhancing workflow. This method may ultimately reduce tiredness and alleviate occupational injuries [28-30].

Various deep learning models have been created using diverse methodologies for the automated assessment of fetal head biometry (head circumference, occipitofrontal diameter, and biparietal diameter) and femur length [31-33]. The automatic measurement of fetal abdominal circumference presents more challenges owing to its uneven morphology and indistinct borders. Consequently, researchers have suggested using object identification or segmentation of fetal abdominal anatomical landmarks (stomach bubble, umbilical vein, fetal spine) before measuring the abdominal circumference [34-38] Recent advancements in artificial intelligence have enabled researchers to create multitasking deep learning models that use segmentation to automatically conduct all biometric measures in the three conventional fetal planes. This strategy allows the DL algorithm to concurrently estimate the GA and GA [39, 40].

The assessment of crown-rump length (CRL) and nuchal translucency (NT) is a crucial component of the prenatal ultrasonography evaluation during the first trimester of gestation [41]. Automatic measurement of CRL and NT via deep learning models has been facilitated by 3D imaging and segmentation methodologies [42-44]. The benefit of using 3D ultrasound is that the deep learning model can identify and choose the optimal planes for conducting biometric measurements of the fetal head, belly, and femur.

For decades, ultrasonography has served as the primary imaging technique for diagnosing prenatal abnormalities. The standard procedure for prenatal ultrasound in evaluating fetal anatomy entails: first, accurate acquisition of standard fetal planes; second, identification and measurement of fetal anatomical structures; and third, categorization of the identified structures as normal or abnormal. Human operators take years of expertise to completely grasp this technique [45]. Conversely, deep learning algorithms may be taught in a very little period using substantial datasets, achieving performance comparable to or superior to that of human operators.

The International Society of Ultrasound in Obstetrics and Gynecology (ISUOG) has recommended many fetal standard planes to standardize the precise acquisition of these planes and minimize intra- and interobserver variability. A comprehensive assessment of fetal anatomy is an arduous and time-intensive endeavor. Deep learning algorithms may be taught to reliably detect several fetal standard planes, and multiple deep learning models have been built to automatically identify the primary fetal standard planes, including the brain, heart, face, and belly. In identifying fetal standard planes, deep learning models that execute object detection and segmentation tasks demonstrate greater accuracy than classification models, as they localize fetal anatomical landmarks prior to classifying the plane, akin to human methodology. Burgos-Artizzu et al. [46] conducted a comparison of 19 deep learning algorithms concerning the accurate identification of four anatomical standard planes (abdomen, brain, femur, and thorax) and discovered that the performance of the top models was comparable to that of a fully trained sonographer, while achieving a classification speed 25 times greater [47-50].

In the second phase, precise identification of normal fetal anatomy is essential to rule out congenital abnormalities. Deep learning algorithms can identify and annotate fetal anatomical components across several standard planes using object recognition and segmentation tasks. Manual structural segmentation is a tedious endeavor, characterized by significant intra- and interobserver heterogeneity. Segmentation deep learning algorithms have shown superior performance compared to both people and other AI models for this task [51].

4. The central nervous system (CNS) of the fetus

The fetal brain is among the most intricate fetal structures, and its examination during the second trimester necessitates the acquisition and assessment of many standard brain planes. Furthermore, the fetal brain experiences significant changes in structure and morphology throughout pregnancy, complicating its evaluation. Multiple deep learning models have been created for the automated detection of standard planes in the embryonic brain and have shown effective performance [52-55]. Deep learning models can accurately recognize several brain anatomical features, including the lateral ventricles, choroid plexus, cavum septi pellucidi, thalami, cerebellum, cisterna magna, Sylvian fissure, and brainstem. Furthermore, deep learning models may be taught to execute automated assessments of fetal brain regions, including the lateral ventricles and cavum septi pellucidi. Another use of deep learning models in brain examination is the evaluation of embryonic cortical development. Deep learning algorithms may evaluate the morphology of cortical structures to predict the associated gestational age; if this gestational age does not align with the actual gestational age, the operator will be notified of a potential cortical developmental defect [56].

Central nervous system (CNS) malformations are among the most common congenital abnormalities. Nevertheless, some CNS abnormalities may not result in significant structural alterations and may remain undiagnosed during prenatal ultrasonography assessments [57,58]. Deep learning might serve as a diagnostic assistance instrument to enhance the detection rates of prenatal brain malformations and assist in the decision-making process. Deep learning models may be taught to identify structural anomalies in the fetal brain or spine on conventional screening planes and notify the operator of the existence and location of potential malformations. Furthermore, deep learning models may categorize the specific kind of abnormality (e.g., ventriculomegaly, intraventricular cyst, non-visualization of cavum septi pellucidi) seen in the fetal picture [59]. Lin et al. [60] revealed the development of a deep learning system capable of localizing and classifying nine distinct brain abnormalities using routine screening planes, with an overall accuracy of 99%.

Accurate evaluation of embryonic heart architecture necessitates the examination of many fetal anatomical landmarks and cardiac structures in well-defined standard planes. Fetal standard cardiac planes, including the four-chamber view, left ventricular outflow tract, right ventricular outflow tract, and three-vessel-and-trachea views, may be automatically obtained via deep learning models [61]. Fetal cardiac structures may be seen using deep learning algorithms that execute object identification or segmentation tasks. Current deep learning models can identify the four distinct chambers of the embryonic heart, as well as the foramen ovale, mitral and tricuspid valves, aorta, apex cordis, moderator band, left and right ventricular walls, interventricular septum, and pulmonary veins [62,63]. DL models could ascertain whether the picture corresponds to the end-systolic or end-diastolic phase of the fetal cardiac cycle based on the opening or closure of the atrioventricular valves. Segmentation deep learning algorithms facilitate the assessment of cardiac morphology by enabling automated quantification of fetal cardiac features, including the dimensions of the fetal heart chambers. It is crucial to note that, in several fetal diseases, including fetal growth restriction, cardiac shape may serve as a marker of pathology [64]. Deep learning models may also be used in the Doppler assessment of the fetal heart, as suggested by Sulas et al. [65]. The authors created a model capable of automatically evaluating pulsed-wave Doppler traces of left ventricular inflows and outflows, identifying early and late diastole and systole. Ultimately, deep learning algorithms may provide biometric heart metrics, including the cardiothoracic ratio and the cardiac axis angle [66,67].

Congenital heart disease (CHD) is the most prevalent birth abnormality and is linked to elevated infant death rates. The prenatal detection of congenital heart disease facilitates early planning and therapy of the problem, hence enhancing perinatal outcomes. Detection rates, however, exhibit significant variability mostly attributable to disparities in operator experience. The use of deep learning models may enhance prenatal identification rates of congenital heart disease by offering an objective and operator-independent evaluation of fetal cardiac pictures. Certain writers have suggested using deep learning models to notify the operator when a cardiac anomaly is observed. Nonetheless, there is a need for deep learning models that can recognize and classify numerous congenital heart defects in the field. As of now, deep learning models capable of identifying hypoplastic left heart syndrome and ventricular septal abnormalities have been developed via object detection or segmentation techniques. Concerning ventricular septal abnormalities, segmentation deep learning algorithms can accurately identify and isolate the whole defect on the fetal heart septum, enabling precise determination of its dimensions [68-70].

The routine assessment of the placenta often includes ascertaining its position and echogenicity, as well as identifying characteristics indicative of aberrant invasive placentation. Placental biometry, associated with fetal smallness, pre-eclampsia, and other negative pregnancy outcomes, is not frequently conducted due to its time-consuming and operator-dependent nature. An entirely automated deep learning model might execute this work swiftly and consistently, therefore reducing interobserver variability, perhaps becoming placental biometry a valuable imaging biomarker [71]. Furthermore, these algorithms may evaluate the placenta's placement (anterior or posterior) and appearance (normal or pathological). Segmentation deep learning methods used with 3D ultrasonography may provide supplementary insights about the anatomy and volume of the placenta [72].

Placental lacunae are hypoechoic cavities located inside the placenta. While prevalent in most pregnancies, extensive, many, and/or irregular placental lacunae may indicate aberrant placental invasion. Abnormal invasive placentation is an obstetric disorder linked to increased maternal morbidity and death. Segmentation deep learning algorithms can effectively identify and localize placental lacunae with high accuracy [73].

A comprehensive prenatal ultrasound examination includes the evaluation of other fetal structures in addition to the brain, heart, and placenta. The use of deep learning (DL) is progressively broadening, with DL algorithms capable of identifying various fetal tissues, including the face, spine, kidneys, lungs, fat tissue, and sexual organs. Certain ultrasound manufacturers have begun including checklists of requisite standard planes and fetal anatomical components into the software of ultrasound machines, to assist and direct the operator throughout the examination [74,75].

5. Deep learning and ultrasonography during childbirth

Ultrasound is being used in the labor ward, proving effective in evaluating fetal head station, degree of bending, and position. Obtaining the accurate picture and doing the requisite measurements may need many minutes, in a context where delays in decision-making might lead to detrimental consequences. The deployment of a deep learning model capable of concurrently evaluating the station, angle, and position of the fetal head may contribute to routine labor ward operations. Research efforts have so far focused on creating deep learning models to evaluate the fetal occiput position during the second stage of labor, classifying it as occiput anterior, posterior, or transverse [76,77].

6. Conclusion

The eventual integration of deep learning in obstetrics and fetal imaging seems unavoidable. Deep learning has several benefits, including objectivity, repeatability, rapidity, and precision, with significant promise as an auxiliary instrument for prenatal ultrasonography. It is essential to recognize that these novel procedures are designed not to supplant specialists in the field, but to assist them and enhance workflow, so conserving time for both patients and clinicians. Furthermore, this technique may enhance healthcare in rural regions or low-income nations, where experienced sonographers are few and patients must traverse considerable distances for consultations. A considerable journey remains before deep learning may be completely integrated into therapeutic practice. Nevertheless, since the volume of papers in the subject increases annually, this may be realized sooner than anticipated.

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