

Review of deep learning and artificial intelligence models in fetal brain magnetic resonance imaging

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Abstract

Central nervous system abnormalities in fetuses are fairly common, happening in 0.1% to 0.2% of live births and in 3% to 6% of stillbirths. So initial detection and categorization of fetal Brain abnormalities are critical. Manually detecting and segmenting fetal brain magnetic resonance imaging (MRI) could be time-consuming, and susceptible to interpreter experience. Artificial intelligence (AI) algorithms and machine learning approaches have a high potential for assisting in the early detection of these problems, improving the diagnosis process and follow-up procedures. The use of AI and machine learning techniques in fetal brain MRI was the subject of this narrative review paper. Using AI, anatomic fetal brain MRI processing has investigated models to predict specific landmarks and segmentation automatically. All gestation age weeks (17-38 wk) and different AI models (mainly Convolutional Neural Network and U-Net) have been used. Some models' accuracy achieved 95% and more. AI could help preprocess and post-process fetal images and reconstruct images. Also, AI can be used for gestational age prediction (with one-week accuracy), fetal brain extraction, fetal brain segmentation, and placenta detection. Some fetal brain linear measurements, such as Cerebral and Bone Biparietal Diameter, have been suggested. Classification of brain pathology was studied using diagonal quadratic discriminates analysis, K-nearest neighbor, random forest, naive Bayes, and radial basis function neural network classifiers. Deep learning methods will become more powerful as more large-scale, labeled datasets become available. Having shared fetal brain MRI datasets is crucial because there aren't many fetal brain pictures available. Also, physicians should be aware of AI's function in fetal brain MRI, particularly neuroradiologists, general radiologists, and perinatologists.

Key Words: Artificial intelligence; Fetal brain; Magnetic resonance imaging; Neuroimaging

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Core Tip: The manual detection and segmentation of fetal brain magnetic resonance imaging (MRI) may be time-consuming, and susceptible to interpreter experience. During the past decade, artificial intelligence (AI) algorithms, particularly deep learning, have made impressive progress in image recognition tasks. A machine learning approach may help detect these problems early and improve the diagnosis and follow-up process. This narrative review paper investigates the role of AI and machine learning methods in fetal brain MRI.

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INTRODUCTION

Role of magnetic resonance imaging for fetal brain imaging

Although sonography is the most used imaging and monitoring technique, magnetic resonance imaging (MRI) is increasingly employed to assess the fetus. Fetal MRI for detecting brain disorders is commonly used with prenatal ultrasound when an anomaly is discovered. Fetal MRI is often requested to research further suspected brain abnormalities such as ventriculomegaly, missing corpus callosum, and posterior fossa anomalies[1]. MRI allows for a more precise and high-quality prenatal brain examination in high-risk fetuses referred from ultrasound. MR images of fetuses can also assist clinicians in detecting brain abnormalities at an early stage of development.

One of the most significant advantages of MRI is visualizing the entire brain, even in late pregnancy. Also, orthogonal sections can be obtained more easily, because the operator can manipulate the direction of spatial encoding gradients at will. With the advancement of rapid MR techniques and MRI software, particularly the half-Fourier acquisition single-shot turbo spin-echo (HASTE) sequence, fetal MR could be conducted without sedation, leading to an increase in the use of this imaging tool[1].

LIMITATION OF "FETAL BRAIN MRI"

Three significant problems with fetal MR imaging affect the quality of the images and the accuracy of the anatomical lines. Throughout the second and third trimesters, gyrification and sulcation transform the fetus's previously smooth surface into a highly complicated structure. Second, the changes in water content that come with active myelination cause MR imaging signal intensity and contrast to varying greatly between gestational age (GAs)[2,3]. Third, fetal MRI acquisitions are more susceptible to imaging artifacts. For example, the images often present motion artifacts caused by the mother's breathing and the fetus's jerky movements. Standing wave artifacts can happen when the conductivity of amniotic fluid and tissues differs. Also, the large field of view (FOV) for the mother's abdomen and the short scan time can lead to lower image resolution, and, thus partial volume effects, in which a single image voxel may contain different types of tissues[4]. These MR artifacts are more prevalent in the imaging of fetuses than those of adults. All three of these problems make it difficult to segment the brain of a fetus on MR images[5].

Deep learning for medical imaging

Deep learning (DL) uses simple interconnected units to extract patterns from data and solve complex problems, specifically on image-related tasks. They have matched or surpassed human performance, although the generally accepted performance for detection is that artificial intelligence (AI+) Radiology is better than either alone. Radiology is a natural application area for DL because it relies on extracting useful information from images. Research in this area has grown rapidly in recent years[6].

The incidence of central nervous system abnormalities in fetuses is rather high, ranging from 0.1% to 0.2% in live births and from 3% to 6% in stillbirths[7]. As a result, initial detection and categorization are critical. There is strong potential for machine learning approaches to assist in the early detection of these problems and enhance the diagnosis and follow-up processes.

Inclusion criteria: We examined how machine learning and AI can be applied to fetal brain MRI. The databases for the search were MEDLINE using PubMed, SCOPUS, Web of Science, EMBASE, Cochrane Library, and Google Scholar, up to June 2022. First, we searched keywords including "artificial intelligence", "machine learning", "deep learning", "Fetal brain", "Fetal MRI", as well as "AI + Fetal", "AI + Brain MRI", and "AI or ML + neonates".

Exclusion criteria: Only relevant AI and Machine Learning methods models in fetal brain MRI were included after the second evaluation. Animal and Basic science studies were also excluded.

We divided models into several applications (Table 1).

AI for preprocessing of fetal images

Obtaining high-quality images of a continually moving subject is one of the most challenging tasks in prenatal imaging. Motion correction and preprocessing technologies can help. Usually, qualified technologists must change acquisition planes frequently and re-acquire sequences. The process is time-consuming and subject to operator variation. Pregnant women who are immobile in a claustrophobic MRI scanner for an extended period may find it difficult. Correction for fetal motion during automated and precise initialization could lead to higher-quality images and potentially a shorter scan time[8].

Gagoski *et al*[9] developed a Convolutional Neural Network (CNN) that automatically detects artifacts on T2 HASTE sequences during fetal MRI to improve image quality[9]. The CNN would evaluate each image slice within an acquisition, and only the slices with the lowest image quality ratings would be re-acquired at the end of the study. This could reduce exam time by only re-acquiring motion-degraded images rather than the entire image stack. Ten healthy pregnant women underwent 73 modified HASTE sequence imaging acquisitions throughout the study. Their real-time implementation of the IQA CNN resulted in an accuracy of 85.2% and an area under the curve of 0.899.

Through DL, Xu *et al*[10] developed a system that detects fetal landmarks automatically[10] (with 15 important locations including upper and lower limb joints, eyes, and bladder) to estimate fetal posture, provide movement tracking of the fetus, and maybe automate the readjustment of acquisition parameters. In less than 1 second, their model could predict fetal posture to the nearest 4.5 mm.

Using a preprocessing AI system (SVRnet), Hou *et al*[11] propose a conceptual method of correcting fetal motion by generating 2-dimensional T2-weighted single slices in varying orientations[11]. They achieved a spatial prediction error of 7 mm on simulated data for moving fetuses around 20 wk of gestation and produced qualitatively enhanced reconstructions. The model is able to solve the 2D/3D registration initialization problem in a broad and computationally efficient way, making it appropriate for usage in real-time settings.

Using DL, Singh *et al*[12] have developed a method for predicting fetal motion directly from acquired images in real-time using anatomical information derived from slice sequences. They trained a recurrent neural network made up of spatial and temporal encoder-decoders to infer motion parameters. They proposed a neural network approach that could predict fetal motion within 8 degrees and estimate motion-corrupted slices to schedule subsequent collections[12].

AI for post-processing of fetal images

Post-processing steps associated with image enhancement and correction include noise reduction, image artifact correction, and image resolution enhancement. DL has recently demonstrated promising results in various research fields, including image enhancement for MRI. Recent publications have demonstrated promising results using DL for MR image enhancement[13].

The lack of normative brain templates and the limited possibilities for automated preprocessing make a quantitative analysis of prenatal brain MRI difficult.

Previously, 3D reconstructions of the embryonic brain required manual delineation of 2D pictures. Li *et al*[14] developed a U-net-based brain extraction algorithm to autonomously segment normal fetal brains using a 5-mm slice fetal MRI in three planes[14]. An average Dice coefficient of 0.97 across all three planes was obtained after spending two to three seconds segmenting each fetal brain.

Ebner *et al*[15] used CNN to automate fetal brain reconstruction through localization, segmentation, and super-resolution[15]. Automated segmentation was comparable to manual segmentation performed by technologists and radiologists on healthy and diseased fetal brains.

AI for reconstruction of fetal imaging

Single-Shot Fast Spin Echo is one example of a fast imaging technique used to acquire low-resolution stacks of 2D slices, which can effectively halt fetal movement. Poor 3D image quality and motion artifacts often emerge from stacks of slices acquired at different times due to patient movement between procedures. For assessment and quantification of fetal brain, from multiple low-resolution stacks acquired from different perspectives, it is desirable to reconstruct a single high-resolution, isotropic volume of fetal brain[12]. The brain must currently be located and extracted from many stacks of 2D slices using time-consuming reconstruction techniques that frequently include user participation.

Table 1 Different applications for artificial intelligence for fetal brain magnetic resonance imaging

Classification		Different applications
A	AI for pre-processing of fetal images	(1) Automatic image quality assessment to detect artifacts on T2 HASTE sequences during fetal MRI (Gagoski <i>et al</i> [9]); (2) Automatically detects fetal landmarks (using 15 key points—upper limb and lower limb joints, eyes, and bladder) (Xu <i>et al</i> [10]); (3) Fetal motion correction (Hou <i>et al</i> [11]); and (4) Predicting fetal motion directly from acquired images in real-time (Singh <i>et al</i> [12])
B	AI for post-processing of fetal images	(1) U-net-based brain extraction algorithm to autonomously segment normal fetal brains (Li <i>et al</i> [14]); and (2) Localize, segment, and perform super-resolution reconstruction for the automated fetal brain (Ebner <i>et al</i> [15])
C	AI for reconstruction of fetal imaging	Fully automatic framework for fetal brain reconstruction, consisting of four stages (Ebner <i>et al</i> [15])
D	AI for gestational age prediction	(1) Predicting GA from fetal brain MRI acquired after the first trimester, which was compared to a BPD (Kojita <i>et al</i> [19]); and (2) An end-to-end, attention-guided deep learning model that predicts GA (Shen <i>et al</i> [20])
E	AI for fetal brain extraction	(1) The automatic brain extraction method for fetal MRI employs a multi-stage 2D U-Net with deep supervision (DS U-net) (Lou <i>et al</i> [24]); and (2) A brain mask for an MRI stack using a two-phase random forest classifier and one estimated high-order Markov random field solution (Ison <i>et al</i> [23])
F	AI for fetal brain segmentation	(1) U-net-like convolutional neural network (Auto-net) (Mohseni Salehi <i>et al</i> [29]); CNN using images with synthetically induced intensity inhomogeneity as data augmentation (Mohseni Salehi <i>et al</i> [29]); (2) Pipeline for performing ICV localization, ICV segmentation, and super-resolution reconstruction in fetal MR data in a sequential manner (Tourbier <i>et al</i> [32]); (3) Automatic method for fetal brain segmentation from MRI data, and a normal volumetric growth chart based on a large cohort (Link <i>et al</i> [33]); (4) Fetal Brain magnetic resonance Acquisition Numerical phantom, to simulate various realistic magnetic resonance images of the fetal brain and its class labels (de Dumast <i>et al</i> [34]); (5) SIMOU-Net, a hybrid network for fetal brain segmentation. Was inspired by the original U-Net fused with the HED network (Rampun <i>et al</i> [36]); and (6) Incorporating spatial and channel dimensions-based multi-scale feature information extractors into its encoding-decoding framework (Long <i>et al</i> [35])
G	AI for fetal brain linear measurement	(1) AI for the anteroposterior (A/P) diameter of the pons and the A/P diameter and S/I height of the vermis (Deng <i>et al</i> [40]); and (2) A fully automatic method that computes three key fetal brain MRI parameters: 1-CBD, 2-BBD, 3-TCD (Avisdris <i>et al</i> [41])
H	AI for automatically localizing fetal anatomy	Automatically localizing fetal anatomy, notably the brain, using extracted superpixels (Alansary <i>et al</i> [42])
I	AI for classification of brain pathology	Classification using several machine-learning classifiers, including DQDA, K-NN, random forest, naive Bayes, and RBF neural network classifiers (Attallah <i>et al</i> [45])
J	AI for placenta detection	(1) U-net-based CNN to separate the uterus and placenta (Shahedi <i>et al</i> [51]); and (2) automatic placenta segmentation by deep learning on different MRI sequences (Spektor-Fadida <i>et al</i> [52])
K	AI for functional fetal brain MRI	An auto-masking model with fMRI preprocessing stages from existing software (Rutherford <i>et al</i> [53])

AI: Artificial intelligence; MRI: Magnetic resonance imaging; RBF: Radial basis function; K-NN: K-nearest neighbor; DQDA: Diagonal quadratic discriminant analysis; CBD: Cerebral Biparietal Diameter; BBD: Bone Biparietal Diameter; TCD: Trans Cerebellum Diameter; S/I: Superior/inferior; SIMOU-Net: Single-Input Multi-Output U-Net; HED: Holistically nested edge detection; BPD: Biparietal diameter; ICV: Intracranial volume.

A fully automatic framework for embryonic brain reconstruction was proposed by Ebner *et al*[15]. A fully automatic framework for embryonic brain reconstruction was proposed by Ebner *et al*[15]: (1) Fetal brain localization using a CNN and coarse segmentation; (2) Another CNN with a multi-scale loss function was used to fine-tune the segmentation; (3) Super-resolution reconstruction with a single parameter that is resilient to outliers; and (4) High-resolution visualization in conventional anatomical space, ideal for diseased brains, is performed quickly and automatically.

For validation, images of fetuses with normal and ventriculomegaly with open spina bifida were used. Each step of their suggested pipeline outperforms cutting-edge methods in comparisons for segmentation and reconstruction, including quality ratings by experienced readers. The results of this technique's reconstruction were on par with those of labor-intensive, manually segmented brains, suggesting that automatic fetal brain reconstruction studies might be applied in clinical settings.

AI for gestational age prediction

The GA assessment of the first trimester is more accurate than dating in the late stages of pregnancy because, as gestation advances, fetal ultrasound measurements have a greater absolute error[16]. MRI provides unparalleled visibility of the fetal brain, enabling the establishment of age-specific morphologic milestones[17,18]. Determining age-appropriate brain development remains challenging due to the fetal brain's continuous development, image quality variation, and motion artifacts' frequent occurrence. DL algorithms offer a powerful way of estimating fetal age from highly variable imaging

data, with moderate to high prediction accuracy to detect GA.

An AI model was created by Kojita *et al*[19] for predicting GA from fetal brain imaging after the first trimester. T2-weighted images from 126 training and 29 validation exams were used to train the DL model. They compared the model with Biparietal Diameter (BPD) model. Compared to the BPD prediction, the model prediction has a significant Lin's concordance correlation coefficient (value = 0.964). As GA grew, the model's and BPD's predictions diverged more from the reference. According to their model, first-trimester ultrasounds can predict GA with a maximum deviation of 1.66 wk, which falls within the range of sonography-based age predictions in the second trimester (7-14 d). After 28 wk of gestation (over 21 d of gestation), these predictions were superior to those based on ultrasound. From 2nd and 3rd trimester fetal brain MR, their DL accurately predicted GA[19]. DL-based prediction of GA could benefit prenatal treatment in underserved first-trimester pregnancies.

Shen *et al*[20] presented an attention-guided DL model that predicts GA. The CNN was trained using 741 normal fetal brains[20]. The recommended regression technique was a machine-enabled automated tool that could better characterize in-utero neurodevelopment and guide real-time GA estimate beyond the first trimester. (concordance correlation coefficient = 0.970, and mean absolute error = 6.7 d).

AI for fetal brain extraction

Prenatal brain MRI reconstruction begins with fetal brain extraction. It is impossible to employ adult brain extraction techniques for fetuses because maternal tissue is present in the MRI of fetal brain tissue. Brain extraction can be difficult due to changes in the size and shape of the developing brain, motion artifacts from fetal movement within the uterus, and substantial variance in the FOV.

Quantitative brain development analysis requires automatic brain tissue segmentation, generally preceded by intracranial volume segmentation (ICV)[21]. The extraction of fetal brains can, however, be difficult because of sparsely collected imaging stacks. Automated segmentation of brain structures is necessary since semi-automatic segmentation is time-consuming and laborious. A variety of strategies exist for automated segmentation or brain extraction from fetal MRIs[22]. The automated brain extraction and oriented positioning of pediatric exams are not yet as developed as for adult exams. They remain challenging given the wide FOV associated with fetal MRI and the large volume of images from repeated acquisitions that are often necessary. As a result, research has been limited to small-scale studies[23].

Lou *et al*[24] proposed a multistage 2D U-Net with deep supervision technique for automatic brain extraction from fetal MRI (DS U-net)[24]. They started by defining a 3D bounding box for localizing the site of the brain using a crude segmentation generated from DS U-net. The deep supervision loss function trains the DS U-net to improve its discrimination capacity. A second DS U-net was then utilized to focus on the extracted region, resulting in sharper segmentation. Advanced segmentation was used to acquire the final segmentation findings. They used 80 training datasets and 43 testing stacks to validate the suggested approach. With an average Dice coefficient of 91.69%, the experimental results confirmed the precision and robustness of their method, surpassing previously proposed strategies.

As opposed to adult studies, automatic brain extraction and orientation are still a challenge in raw fetal MRI volumes with a wide FOV. Ison *et al*[23] provided a methodology for automatic fetal brain extraction and orientation that overcomes this constraint[23]. A two-phase random forest classifier and a high-order Markov random field solution were used to produce a brain mask for an MRI stack. The extraction that resulted had a detection rate of 98%. Furthermore, when tested on cases ranging in gestational weeks from 18 to 30.2, the mean sensitivity was 88%, indicating a solid pipeline to automated fetal MRI processing procedures.

AI for fetal brain segmentation

Fetal MRI volumetric and morphologic analysis begins with brain segmentation. Because manual segmentation is expensive and time-consuming, automated segmentation could greatly simplify the process. Due to increased intensity inhomogeneity and spontaneous fetal movements, automated brain tissue segmentation in prenatal MRI is difficult.

Different segmentation strategies for automatic delineation of the fetal brain MRI have recently been proposed. Unsupervised, parametric, classification, atlas fusion, and deformable models were used to evaluate the segmentation. In the segmentation procedure, brain atlases are frequently used as training data[25].

However, difficulties with image capture, continuous brain development, and the shortage of imaging data obstruct this segmentation process. Makropoulos *et al*'s paper showed the various segmentation approaches for each category[25]. The use of CNN has gained popularity in recent years for the automatic segmentation of medical images[26]. There have been several studies that investigated different CNN architectures in order to segment brain tissue using adult MRIs[27,28].

Also, Mohseni Salehi *et al*[29] suggested a DL segmentation method that is iterative and employs a U-net-like CNN (Auto-net)[29]. ITK-SNAP software segmented the fetal brain from a manual bounding box[30].

According to Khalili *et al*[31], segmentation can be done with a CNN using images augmented with synthetically induced intensity inhomogeneity rather than with approaches that estimate the bias field prior to segmenting[31]. First, a CNN was used to extract the intracranial volume of the patient. The

collected volume is then segmented into seven brain tissue classes using another CNN with an analogous architecture. A mixture of linear gradients with random offsets and orientations was added to the training data to make a method that worked with slices showing intensity inhomogeneity artifacts. When generated intensity inhomogeneity artifacts enriched the training data, mean squared displacement dropped from 0.78 mm to 0.37 mm and DC overall tissue classifications improved from 0.77 to 0.88. These findings showed that the suggested method might replace or augment preprocessing processes such as bias field adjustments, resulting in better segmentation performance.

Several methods first find the location of the brain in the fetal ICV, which is different from methods that do ICV segmentation without brain localization. Using fetal MR data, Tourbier *et al*[32] propose a pipeline for localizing, segmenting, and reconstructing ICVs sequentially[32]. Using age as prior knowledge, this strategy segmented the ICV in fetal MRI. Template-based approaches have the disadvantage of being computationally more expensive than machine learning algorithms. Significant segmentation errors are likely to occur if representative age-matched templates are unavailable. Furthermore, brain localization approaches require the ICV to be segmented afterward to separate brain tissue classes.

Link *et al*[33] developed a semi-automatic fetal brain segmentation approach utilizing MRI data and a normal volumetric growth chart based on a large cohort to generate an automatic method for clinical use. They used MRI data from 199 usually growing fetuses to construct the Seeded Region Growing algorithm (18-37 wk)[33]. Their model strongly correlates ($r^2 = 0.9183$, $P = 0.001$) with manual segmentation. Differences in mean volume and volume overlap were 4.77 and 18.13 percent, respectively. They described their procedure as quick, accurate, repeatable, and user-independent.

Automated multi-tissue fetal brain segmentation algorithms are being developed to assess the human brain's development in utero quantitatively. However, the available annotated fetal brain datasets have limitations in number and heterogeneity, hampering domain adaptation strategies for robust segmentation. FaBiAN, a Fetal Brain Magnetic Resonance Acquisition Numerical Phantom, was utilized by de Dumast *et al*[34] to recreate a variety of accurate magnetic resonance images of the fetal brain and its class labels[34]. They showed that these multiple synthetic annotated data, created for free and then reconstructed using the target super-resolution technique, can be utilized to successfully domain adapt a DL method that segments seven brain tissues. The segmentation accuracy was improved overall, particularly in the cortical gray matter, white matter, cerebellum, deep gray matter, and brain stem.

Example of segmentation: "Expanding the Unet model": U-Net is a popular CNN used for segmenting MR images due to its precision. While U-net often performs well, its performance is often limited by the subtle differences between segments in MRI, as well as the loss of information caused by downsampling and upsampling. One method for solving this problem is to employ a spatial and channel dimension-based framework. The encoding part enhances multi-scale features, while the decoding part recovers the corresponding localization to a higher resolution layer[35]. There have been two proposed methods for extracting multiscale features: Multi-branch pooling and multi-branch dense prediction. A multi-branch output structure is created in the decoding section by combining dense nearby prediction features at various scales.

The hybrid network known as the Single-Input Multi-Output U-Net (SIMOU-Net) was also developed by Rampun *et al*[36] for the purpose of fetal brain segmentation. The original U-Net and the holistically nested edge detection network were the basis for this model[36].

SIMOU-Net has a deeper architecture than U-Net, and takes account of all side outputs. In a similar way, it acts as a neural ensemble. By combining outputs from a single network instead of averaging the results of several independent models, their approach reduced the variance and generalization error of predictions. 200 normal fetal brains with over 11500 2D pictures revealed Dice $94.2 \pm 5.9\%$ In 54 abnormal cases, the suggested network achieved Dice of $91.2 \pm 6.8\%$.

A meaningful interpretation of the fetal brain requires brain segmentation. It is essential to accurately segment brain tissue on an MRI for diagnosis, therapy planning, and neurologic state monitoring.

AI for fetal brain linear measurement

Routine clinical assessment of fetal brain development using MRI is mainly subjective, with a few biometric linear measurements. Based on MRI reference growth centiles of normal-developing fetuses, these measurements are compared to those taken in the United States.

Taking manual measurements requires clinician training, takes a lot of time, and is subject to inter-observer and intraobserver variability[37]. In some cases, small measurement errors can pose a risk of misdiagnosis or mismanagement of pregnancy[38]. Several technical challenges involve developing automatic methods for calculating biometric fetal brain measurements. First, the method should follow the guidelines and steps explicitly and implicitly performed by the clinician, including localizing the fetal brain in the MRI volume, selecting the reference slice, and identifying the anatomical landmarks and measurements. MRI scanning planes, resolutions, contrasts, and procedures, fetal brain pathology, and motion artifacts all result in inaccurate observations and observer variability[39].

Deng *et al*[40] at Rush University made a new AI model to find two important fetal biometric parameters from fetal brain MRI: The anteroposterior (A/P) diameter of the pons and the A/P diameter and superior/inferior height of the vermis[40]. There were 55 fetal brains MRI patients and about 100

sets of sagittal T2-weighted HASTE brain images. They made U-net DL model to find six landmarks: Two on the pons and four on the vermis. The steps that were taken were: (1) Image selection and labeling by a neuroradiologist; (2) Dataset augmentation (adding noise, rotating, flipping); (3) Region of interest (ROI) masking and use of the transforming process (Gaussian distribution); and (4) Using the U-net model to find landmarks (Pons-vermis). Both landmarks (2 for pons and 4 for vermis) and four-fold cross-validations were taught to the models simultaneously.

They devised two models of 4-fold cross-validation (by GA weeks or by mixed weeks), and mixed cross-validation was the most accurate (98 and for pons and 88% for vermis). The most accurate measurements were: 100% for the pons; 97.5% for the A/P diameter of the vermis; and 95% for the height of the vermis.

The average accuracy was 98% for Pons1, 99% for Pons2, 98% for Vermis1, 84% for Vermis2, 86% for Hvermis1, and 86% for Hvermis2.

In 2021, Avisdris *et al*[41] studied a new deep-learning method to automatically compute linear measurements in a fetal brain MRI volume based on landmark detection and estimates[41]. This was a fully automatic method that computes three key fetal brain MRI parameters: (1) Cerebral Biparietal Diameter (CBD); (2) Bone Biparietal Diameter (BBD); and (3) Trans Cerebellum Diameter (TCD). Compared to the measurement of an expert (fetal radiologist), their model has yielded a 95% confidence interval agreement of 3.70 mm for CBD, 2.20 mm for BBD, and 2.40 mm for TCD. The authors proposed that their model surpasses previously published results and suggested that this model to be directly applied to other linear measurements.

Their approach consists of four steps: (1) Detection of the ROI with a two-stage anisotropic U-Net; (2) Selection of reference with a CNN; (3) Computation of linear measurement according to landmarks detection with a novel CNN, FMLNet; and (4) Finally, estimation the reliability with a Gaussian Mixture Model. Their model requires fetal brain structure segmentation and is considered robust based on reliability estimation.

Using deep neural networks, Avisdris *et al*[39] proposed an algorithm that performs automatic linear measurements of the fetal brain[39]. The outputs were the measurement values and reference slices in which the measurements were computed. The method, which follows the manual measurements principle, consisted of five stages: (1) Computation of a ROI that includes the fetal brain with an anisotropic 3D U-Net classifier; (2) CNN reference slice selection; (3) Multiclass U-Net classifier slice-wise fetal brain structures segmentation; (4) Fetal brain mid-sagittal line computation; and (5) Measurements. Testing findings on 214 volumes for CBD, BBD, and TCD measures showed a mean L1 difference of 1.55 mm, 1.45 mm, and 1.23 mm, respectively. This automatic method for computing biometric linear measurements of the fetal brain from MR imaging achieved human-level performance, and the authors suggested that it can help assess fetal brain biometry in normal and pathological cases.

AI for automatically localizing fetal anatomy

In MR scans, the location and orientation of the fetus are subject to substantial change. In contrast to standard adult MRI, where the anatomical planes are aligned, these fetal images are difficult to analyze and interpret.

By automatically locating fetal anatomy, including the brain, Alansary *et al*[42] addressed the problem. Using dense scale-invariant feature transform descriptors, they first extracted superpixels, then computed histograms for each superpixel[42]. To discriminate between the brain and non-brain superpixels, they built a superpixel graph and trained a random forest classifier. The framework was tested on 55 MR datasets aged 20 to 38 wk. Using 5-fold cross-validation, the proposed technique was found to have a brain detection accuracy rate of 94.55%

AI for classification of brain pathology

Recently, machine learning techniques have been used to detect fetal brain MRI images and identify and classify these abnormalities[43]. In most early studies of fetal brain images, anomalies were detected by segmenting the images. Only a few studies have examined how machine-learning approaches detect prenatal brain abnormalities[25,44].

A new scheme for organizing fetal brains was proposed by Attallah *et al*[45]. For this purpose, she used several machine-learning classifiers, including K-nearest neighbor (KNN), random forest, and naive Bayes. Bagging and AdaBoosting ensemble models were created using random forest, naive Bayes, and RBF network classifiers. They suggested that this new technique may successfully identify and classify various abnormalities in MRI images of the fetal brain of different GAs. KNN classifiers had the highest classification accuracy (95.6%) and area under receiving operational characteristics (99%). Ensemble classifiers improved model outcomes[45].

Using DL methods, Attallah *et al*[45] suggested a four-step approach for the early diagnosis of Embryonic Neurodevelopmental Disorders (END): Learn-from-previous-experience, deep feature extraction, feature reduction, and classification. The study included three experiments. An end-to-end DL strategy was employed in the first experiment with three CNN structures. As part of experiment II, deep features were extracted from each DCNN's FC layer in order to train support vector machine (SVM) classifiers one by one. These features were reduced using Principal Component Analysis and used to generate various SVM classifiers. Deep features were put together to see how they affected

classification performance, and the best features were selected to improve performance. The proposed framework results showed that it could find ENDS with high accuracy. The authors suggested that their algorithm can assist neuroradiologists in diagnosing fetal brain abnormality, facilitating treatment planning, and follow-up as well as informing the parents of the embryonic conditions. This can reduce the occurrence of NDs among newborns, improving the quality of health management[46].

AI for placenta detection

The placenta plays an important role in maternal-fetal health, but limited non-invasive tools exist to assess placental function in utero[47]. Placental segmentation has been shown to assist in detecting and quantifying pregnancy-related problems such as placenta accreta and growth restriction[48].

MRI is an alternative imaging modality that can be used to quantify placental development in healthy and growth-restricted pregnancies. High-risk pregnancies have shown anomalies in placenta volume, thickness, and intensity on 2-dimensional MRIs[49,50].

Shahedi *et al*[51] differentiate the uterus and placenta in 100 pregnant women using a U-net-based CNN with DICE coefficients of 0.92 and 0.82[51]. Only a few user inputs (reportedly seven 'clicks') are required to obtain the output placental size and placement.

In a recent study, Specktor-Fadida *et al*[52] presented a method for segmenting the placenta using DL on different sequences of MRI[52]. Specktor-Fadida *et al*[52] developed a DL technique for automatically segmenting placentas on various MRI sequences. Placenta ROI detection and segmentation networks use a new loss function based on a contour and a soft Dice. On 21 test cases and only 16 training cases, the experimental Dice score for the FIESTA sequence was 0.847. Switching to the TRUFI sequence improved Dice scores on 15 test cases to 0.78. Sequence transfer bootstrapping and contour Dice loss and self-training led to the best placenta segmentation results ever.

AI for functional fetal brain MRI

Prenatal brain development can now be assessed using resting-state functional MRI (rs-fMRI). Despite this approach's rapid and widespread adoption, we lack neuroimaging processing pipelines to handle this data format's unique issues. The most challenging part of the processing is isolating the fetal brain from the rest of the tissue in hundreds of moving 3D brain volumes. Rutherford *et al*[53] trained a CNN using 1241 manually traced fetal fMRI. It performed well on two held-out test sets from different MR scanners and patients. They also added fMRI preprocessing stages from existing software to the auto-masking model[53].

MRI 3T vs 1.5 T in fetal MRI: Using 3-T magnets has improved access to advanced imaging sequences and anatomical evaluation in fetal MRI. 3.0-T MRIs have better spatial resolution and signal-to-noise ratios than 1.5-T ones. However, when it comes to fetal MRI, there are concerns about the possibility of the fetus receiving greater radiofrequency energy. Most fetal 1.5- and 3.0-T MRIs had similar energy metrics. Three-dimensional steady-state free precession and two-dimensional T1-weighted spoiled gradient echo may need modifications to reduce patient-delivered energy.

LIMITATIONS OF "AI IN FETAL MRI"

DL-based AI tools require many annotated training datasets to produce acceptably accurate results, which often have limited availability in terms of the dataset. In addition, it is difficult to constantly update models as training data increase and practice patterns change. Among the many DL-based fetal MRI algorithms that have been proposed and are under current development, it remains to be determined which ones possess the potential for widespread adoption. Thus, radiologists should collaborate with AI researchers to understand the latest methods and provide clinical feedback to guide future development. AI tools will likely act as powerful image-processing and decision-support tools to improve radiologists' accuracy and efficiency, not their replacement.

DL methods are anticipated to become more powerful as more large-scale datasets with labels are available. Fetal brain MRI datasets that share data, such as the FeTA Dataset, are crucial due to the scarcity of fetal brain images[54]. Automatic multi-tissue fetal brain segmentation algorithms are needed to facilitate this analysis, requiring open datasets of segmented fetal brains.

CONCLUSION

Several DL-based strategies have been developed to predict specific landmarks and perform automatic segmentation in fetal MRI applications. All gestation age weeks after first trimester[16-37] where various AI models have been suggested (most notably CNN and U-Net). Some models have achieved an accuracy of 95% or higher. AI tools could be deployed in the preprocessing, the post-processing, as well as the reconstruction of fetal MR images. It is also possible to predict GA with an accuracy of one week, extract the fetal brain, segment the fetal brain, and detect the placenta with the help of AI algorithms.

Some linear measurements of the fetal brain have been proposed; these include the cerebellar diameter, the transcerebellar diameter, and the BPD.

As a result of the limited number of publicly available fetal brain MRI data sets, the development of AI algorithms is challenging at this point, but the developments so far have been promising. Research in these fields will continue to rely on the further development of public data sets and the collaborative efforts between physicians (specifically neuroradiologists, general radiologists, and perinatologists) and researchers in this field.

FOOTNOTES

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