

Use of Artificial Intelligence in Fetal Brain Ultrasound Examination: A review

Yuanjie Cui^a, Cuixia Guo^a, Zhen Li^a, Juan Zhang^a, Yuting Wu^a, Qingqing Wu^a, Lijuan Sun^{a,*}

^a Department of Ultrasound, Beijing Obstetrics and Gynecology Hospital, Capital Medical University. Beijing Maternal and Child Health Care Hospital. Beijing, China

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Abstract: Ultrasound has become the primary modality for fetal central nervous system examination and diagnosing malformations. However, the effectiveness of fetal brain examinations remains highly operator-dependent. Deep learning, a key branch of artificial intelligence (AI), has demonstrated significant advantages in image recognition, proving particularly valuable in medical imaging. Consequently, several studies have proposed the use of deep learning models as tools for fetal brain ultrasound examinations. AI has achieved clinical applications in fetal brain ultrasonography, encompassing standard plane recognition, biometric measurements, structural identification, and malformation diagnosis. This review systematically analyzes the applications of AI in fetal brain ultrasound examination and discusses unmet clinical needs and future development.

Key words: Artificial intelligence; Fetal brain; Obstetric ultrasound; Deep learning

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Artificial intelligence (AI) is the capability of computer programs to execute processes associated with human intelligence, including reasoning, learning, thinking [1]. As a subset of AI, Machine learning (ML) trains algorithms to identify patterns using human-defined reasoning rules [2]. Deep learning (DL), an advanced ML, excels in image recognition and classification. This capability proves particularly valuable for medical imaging analysis [3,4], including ultrasonography [5,6]. Among DL architectures, convolutional neural networks (CNNs) predominate in image processing. CNNs analyze large datasets through pattern recognition to extract features through convolutional layers and reduce feature dimensions via pooling layers. It can extract important features from images, such as ventricles, hemispheres, and sulci [7,8]. U-Net consists of an encoder and to compress the image to extract features and a corresponding decoder, which reconstruct it to produce a segmentation map, then using to preserve details and improve segmentation accuracy. U-Nets are suitable for image segmentation such as the

segmentation of cerebellum [9,10]. DL models are developed using either supervised or unsupervised learning approaches. Supervised DL models (the prevalent approach), require labeled data. During testing, these models predict classifications for unlabeled data based on learned representations. Conversely, unsupervised learning techniques operate without predefined labels, with models autonomously identifying latent patterns to categorize images.

Fetal structural anomaly detection constitutes a critical component of prenatal examination. According to the ISUOG guidelines [11], most fetal anatomical structures undergo key developmental changes between 18 and 22 gestational weeks. During this period, a systematic ultrasound examination encompasses the assessment of fetal structures such as the brain, face, neck, chest, heart, abdomen, as well as fetal appendages. The prenatal examination of some structures is challenging due to their rapid changes throughout pregnancy and complexity, such as the fetal heart and brain. Central nervous system (CNS) anomalies represent the second

* Corresponding author: Department of Ultrasound, Beijing Obstetrics and Gynecology Hospital, Capital Medical University, No.251 Yaojiayuan Road, Chaoyang District, Beijing, China. (Lijuan Sun)
e-mail: sunlijuan@ccmu.edu.cn (LJ S)

most prevalent congenital disorder after cardiac malformations, with longitudinal studies reporting incidence rates approaching 1% [12,13]. However, ultrasound diagnosis rate for cerebral malformations is only 68%, with most diagnoses occurring during the mid-gestational period [14]. These CNS anomalies constitute major etiologies for both intrauterine demise and postnatal neurodevelopmental impairment [13].

Ultrasound image analysis in clinical practice faces significant challenges arising from equipment settings, fetal motion artifacts, anatomical obstruction, examiner expertise, and gestational age-related variation. [15–18]. Convolutional neural networks (CNNs) have demonstrated the clinical utility in ultrasonography, including the AI-assisted diagnoses of Hashimoto's thyroiditis and ovarian cancer [19,20]. In fetal prenatal examination, AI is mainly applied for standard-plane detection, biometric measurements, recognition of structures, three-dimensional Ultrasound(3D-US) segmentation, and malformation diagnosis [21,22].

Standard-plane Detection

In fetal brain ultrasound examination, the assessment of brain development is crucial for assessing fetal growth and diagnosing abnormalities. Current clinical protocols prioritize mid-trimester neurosonography to acquire and analyze key standard planes [23,24]. Some studies have demonstrated the efficacy of DL in standard-plane detection with high accuracy [25–28]. Qu et al. pioneered a differential-CNN model identifying six essential fetal brain planes (transventricular, transthalamic, transcerebellar, mid-sagittal, parasagittal, anterior coronal) at 92.93% accuracy [26]. Liang and Kong et al. further advanced this field by employing DenseNet architectures for comprehensive standard plane detection, including fetal head positioning [29,30]. The incorporation of attention mechanisms has further improved both detection performance and clinical interpretability. By mimicking sonographers' visual attention patterns,

Cai et al. designed the Temporal SonoEyeNet (TSEN), a multi-task neural network incorporating eye-tracking data to optimize detection of the transventricular plane [27]. Notably, conventional classification CNNs may inadequately replicate clinical workflows. A more clinically aligned approach involves anatomical structure-based plane localization. Lin and Zhang et al. implemented region-based CNNs (R-CNN) with multi-task learning to detect critical intracranial structures: cavum septi pellucidi (CSP), thalamus, third ventricle, cerebral midline, Sylvian fissure, and choroid plexus—enabling precise plane identification and quality control [25,31]. Table 1 summarizes the studies reviewed in this section. These AI-driven innovations significantly improve examination efficiency, reducing operator fatigue and patient discomfort associated with prolonged examination. By bridging technical capabilities with clinical workflows, DL-powered neurosonography is establishing new standards for prenatal CNS evaluation.

Biometric Measurement

Fetal biometric measurements—including head circumference (HC), biparietal diameter (BPD), abdominal circumference (AC), and femur length (FL)—provide essential parameters for gestational age (GA) estimation and fetal weight prediction in prenatal management [32]. Foi et al. pioneered the DoGell (Difference of Gaussians revolved along Elliptical paths) algorithm for automated fetal skull recognition in 2D ultrasound images, enabling simultaneous BPD, HC, and occipitofrontal diameter (OFD) quantification [33]. With the increasing use of AI, CNN-based fetal head segmentation methodologies continue to evolve. Sinclair et al. achieved expert-level performance using Fully Convolutional Networks (FCNs) for automated HC and BPD measurement [34]. Zeng et al. integrated attention mechanisms and deep supervision strategies into the V-Net model, proposing the deeply supervised attention-gated (DAG) V-Net, which demonstrated better performance than tra-

Table 1 Summary of artificial intelligence algorithms for fetal brain standard-plane detection

Paper	Model architecture	Plane	Dataset size	Performance metrics (For fetal brain)
Zhang 2021	Feature Extraction Network, Region Proposal Network and Class Prediction Network	FASP, FBSP, 4CH	3280 2D	Prec = 0.95, Sen = 0.92, ACC = 0.95
Qu 2020	differential-CNN	FBSPs	19142 2D	Prec = 0.93, Rec = 0.92, ACC = 0.93
Cai 2020	Temporal SonoEyeNet (TSEN)	FBSP, FASP, FFESP	280 Videos	Vecsim = 0.98, Pre = 0.89, Rec = 0.85
Kong 2018	multi-scale dense networks (MSDNet)	FBSP, FASP, 4CH, FFSPs	22715 2D	Pre = 1.00, Rec = 1.00
Liang 2019	SPRNet	4CH, FASP, FBSP, FFASP, coronal FFSP	22295 2D	ACC = 0.99, Sen = 0.99, Spe = 0.99
Lin 2019	MF R-CNN	FBSP	1771 2D	ACC = 0.93, Prec = 0.89 Sen = 0.96

FASP, fetal abdomen standard plane; FFSP, fetal facial standard plane; FFASP, fetal face axial standard plane; 4CH, four chamber view; FBSP, fetal brain standard plane; FFESP, fetal femur standard plane; CNN, convolutional neural network; 2D, two-dimensional ultrasound; ACC, accuracy; Rec, recall; Sen, sensitivity; Spe, specificity

ditional U-Net and V-Net models on the HC18 dataset [35]. Early-pregnancy research predominantly focuses on HC measurement. Van den Heuvel et al. developed a machine learning-based computer-aided detection (CAD) system for the automated measurement of HC in early pregnancy [36,37]. In methods of automated HC measurement with DL, there are segmentation and non-segmentation approaches. The segmentation method uses CNNs to segment the image and then fits an ellipse to estimate HC, while the non-segmentation method uses regression CNNs to directly estimate HC. Zhang et al. demonstrated superior accuracy with segmentation methods, though regression CNNs show promising future potential [36]. While most automated measurements utilize single-frame images, Szymon Plotka et al. introduced FUVAI—a multi-task CNN-based spatio-temporal fetal ultrasound feature extraction and standard plane detection algorithm, enabling video-based standard plane detection and biometric measurement comparable to expert sonographers [38]. Beyond BPD and HC measurement, current research has begun to focus on measuring other cranial structures, such as the cerebellar diameter, the width of lateral ventricles and CSP [39–41]. Chen et al. achieved manual-equivalent accuracy in lateral ventricle measurement [40].

GA estimation is crucial for pregnancy management. In addition to the HC, BPD, AC, and FL, Namburete et al. employed the regression forest method to analyze the spatiotemporal correlation between brain maturation and GA in fetal cranial ultrasound images, and established a feature selection framework based on 3D ultrasound brain image of 447 fetuses, identifying GA-sensitive neuroanatomical features, including the Sylvian fissure

and the cingulate and callosal sulci [41]. Wyburd et al. implemented a VGG-NET with an attention mechanism to estimate GA by evaluating the fetal Sylvian fissure, calcarine sulcus, and parieto-occipital sulcus [42]. Table 2 summarizes the research for biometric measurement that are surveyed in this section.

Recognition of Structures and 3D Segmentation

While 3D ultrasound is recommended in fetal neurosonography guidelines [23,24], its diagnostic utility remains limited by significant operator-skill dependency and inter-observer variability [43]. Automation and AI offer promising solutions. Some manufacturers have already provided related software, such as 5D CNS+™ and SonoCNS™, which provide semi-automated plane reconstruction and measurement of fetal brain ultrasound [44,45]. Based on the software, researchers have developed fully automated 3D U-Net architectures for volumetric data segmentation. One such implementation—intelligent navigation-based fully automated 5DCNS+™—enables rapid reconstruction of nine standard fetal brain planes from volumetric data based on the transthalamic plane [46]. Beyond plane reconstruction, AI facilitates 3D structural segmentation and localization, Huang et al. segmented and located five structures (lateral ventricles, cavum septi pellucidi, thalamus, cerebellum, and the) using 3D U-Net with extracranial tissues masking. Wyburd et al. applied 3D U-Net to fetal cortical plate segmentation, while Venturini et al. also used 3D U-Net to segment the fetal thalamus, brainstem, cerebellum, and white matter [47,48]. Wu et al.

Table 2 Summary of artificial intelligence algorithms for biometric measurement of fetal brain

Paper	Model architecture	Biometry	Dataset size	Performance metrics
Foi 2014	Difference of Gaussians revolved along Elliptical paths	BPD, HC, OFD	90 2D	DSC = 0.98, MSD = 2.3 mm
Sinclair 2018	Fully Convolutional Networks (FCN)	HC, BPD	HC18	DSC = 0.98
Zeng 2021	DAG) V-Net	HC	HC18	DSC = 0.98, MAE = 1.77 mm
Zhang 2022	Regression CNN Model, CNN Segmentation Model	HC	HC18	MAE = 1.08 mm (Segmentation) vs. 1.83 mm (Regression)
van den Heuvel 2018	Random Forest Classifier, Hough transform, Dynamic Programming, Ellipse fit	HC	1334 2D	DSC = 0.97, MAE = 2.8 mm
Plotka 2022	U-Net	BPD, HC, AC, FL	750 videos	DSC = 0.96, MAE = 1.04, (HC), 0.27 (BPD)
Pluym 2021	SonoCNS	BPD, HC, TCD, CM, Vp	143 women	ICC of the automated approach compared to the manual measurements for BPD (0.81), HC (0.88), TCD (0.50), CM (0.23), Vp (0.26)
Chen 2020	Mask R-CNN	lateral ventricles	2900 2D	MAE = 1.8 mm, ATC = 0.13 s
Namburete 2015	Regression forest	GA	635 3D	RMSE = 6.10 days, $r = 0.98$
Wyburd 2021	CNN	SF, POF, CLC	811 3D	MAE = 4.1 (SF), 5.1 (POF), 4.9 (CLC)

DSC, dice similarity coefficient; MSD, maximum symmetric contour distance; MAE, mean absolute error; ATC, average time consumed; RMSE, root-mean-squared error; SF, sylvian fissure; POF, parieto-occipital fissure; CLC, calcarine sulcus; HC, head circumference; BPD, biparietal diameter; AC, abdominal circumference; FL, femur length; TCD, transcerebellar diameter; CM, cisterna magna; Vp, posterior horn of the lateral ventricle; CNN, convolutional neural network; GA, gestation age; 2D, two-dimensional ultrasound; 3D, three-dimensional ultrasound.

enhanced U-Net with attention modules for CSP segmentation/measurement to detect neurodevelopmental anomalies [49]. In addition to 3D segmentation, Wang et al. proposed a DL-based MCANet to segment the middle cerebral artery and assist sonographers in locating the sample gate on Doppler ultrasound [50]. Table 3 shows a summary of the literature covered for the recognition of structures and 3D segmentation.

Malformation Diagnosis

Currently, CNNs are the primary algorithm employed in models for the diagnosis of CNS malformations. Xie et al. demonstrated that the preliminary diagnosis of intracranial malformations could be made by identifying the three axial planes transventricular plane, transcerebellar plane and transthalamic plane) [51]. This model used U-Net with dilated convolutions for brain structure segmentation and employs a VGG-19 model which was pre-trained on ImageNet, to classify normal and abnormal images. The Gradient-weighted Class Activation Mapping Grad-CAM) algorithm was used to visualize the regions where the algorithm is most activated, which are then manually verified to assess the accuracy of the algorithm in recognizing abnormal regions. Grad-CAM is a visualization technique that generates class-specific heatmaps to highlight the image regions most influential in a CNN's decision. Xie et al. validated the feasibility of CNNs for classifying normal or abnormal three axial standard planes of fetal brain [52]. Lin et al. developed a CNN-based system called PAICS Prenatal Ultrasound Diagnosis Artificial Intelligence Conduct System). The system achieved 95% diagnostic accuracy in detecting nine distinct intracranial malformations non-visualization of the CSP; non-visualization of the septum pellucidum; crescent-shaped single ventricle; mild ventriculomegaly; severe ventriculomegaly; non-intraventricular cyst; intraventricular cyst; open fourth ventricle; and mega cisterna magna) from real-time ultrasound images [53]. This research team demonstrated that the PAICS could improve sonol-

ogists' performance in detecting fetal intracranial malformations through a comparison of diagnosis accuracy by 36 sonologists at different expertise level, using three modes without PAICS assistance, using PAICS at the beginning of the assessment, and using PAICS after a fully unaided interpretation) [54]. Direct head-to-head comparisons of AI models for fetal brain anomaly detection on ultrasound remain limited. A few recent studies have compared conventional CNNs, separable CNNs, and Xception-based models, whereas most existing studies evaluate a single architecture on ultrasound datasets. By employing depthwise separable convolutions to decouple spatial and channel information, Xception has demonstrated superior performance in anomaly diagnosis compared with standard CNN, even with a limited training iterations [55].

However, these CNNs models are based on supervised learning, which requires labels of specific anatomical structures. This process involves extensive data collection and preprocessing. Several studies presented denoising diffusion probabilistic models (DDPMs) in detection of fetal brain anomalies. DDPMs are trained exclusively on normal fetal brain ultrasound images, learning the generative process that reconstructs healthy anatomy from noisy inputs. During inference, abnormal structures deviate from this learned distribution, producing detectable reconstruction errors. These studies evaluated the performance of the model in fetal brain anomaly detection and influence of different type and levels of noisy, demonstrating the potential of unsupervised learning for detecting fetal brain anomalies without requiring labeled data with the Area Under the Precision-Recall Curve of 79.8% [56,57]. Table 4 provides a structured summary of the surveyed literature for the CNS malformation diagnosis.

Limitations and Future Perspectives

The fetal brain represents one of the most complex fetal structures. To date, the large-scale clinical studies evaluating the real-world application of artificial intelli-

Table 3 Summary of artificial intelligence algorithms for recognition of structures and 3D segmentation of fetal brain

Paper	Model architecture	Plane/Structure	Dataset size	Performance metrics
Welp 2020	SDCNS+	MSP, TT, TV, TC, TFc, TCaucd, TTc, TCc, PSP	1019 3D	999/1019 (98%) of the volumes, ≥ 8 planes were sufficiently visualized, 958/1019 (94%) all nine planes were sufficiently visualized
Wyburd 2020	U-Net	cortical plate	307 fetuses	DSC = 0.82
Venturini 2019	DAG V-Net	HC	528 3D	DSC = 0.81 (thalamus), 0.82 (brainstem), 0.77 (cerebellum), 0.92 (white matter)
Wu 2020	U-Net	CSP	448 2D	DSC = 0.77, Pre = 0.79
Wang 2018	MCANet	MCA	4005 2D	DSC = 0.77

MSP, midsagittal plane; TT, transthalamic plane; TV, transventricular plane; TC, transcerebellar plane; TFc, transfrontal plane (coronal); TCaucd, transcaudate plane (coronal); TTc, transthalamic plane (coronal); TCc, transcerebellar plane (coronal); PSP, parasagittal plane; 3D, three-dimensional ultrasound; 2D, two-dimensional ultrasound; CSP, cavum septi pellucidi; MCA, middle cerebral artery; HC, head circumference

Table 4 Summary of artificial intelligence algorithms for malformation diagnosis

Paper	Model architecture	Malformation	Dataset size	Performance metrics
Xie 2020	CNN	Ventriculomegaly, hydrocephalus, Blake pouch cyst, Dandy–Walker malformations, cerebellar vermis hypoplasia	54990 2D	DSC = 0.942 (craniocerebral region segmentation), average F1-score=0.96 on classification, average mean IOU of 0.497 on lesion localization
Xie 2020	CNN	Binary classification as normal or abnormal	29419 2D	ACC = 0.96, Sen = 0.97, Spe = 0.96, AUC = 0.99
Lin 2022	PAICS	Normal and 9 intracranial malformations	43890 2D, 169 Video	Macro- and microaverage AUC = 0.93 and 0.98 (e internal validation image dataset), 0.90 and 0.90 (e external validation image dataset), 0.97 and 0.98 (real-time scan setting)
Shirsat 2025	CNN	Normal and 15 intracranial malformations	1786 2D	ACC = 0.54 (Standard CNN), 0.63 (Separable CNN), 0.88 (Xception); Prec = 0.54 (Standard CNN), 0.56 (Separable CNN), 0.89 (Xception)
Olsen 2024	DDPM-iNAAD	Intracranial malformations	14760 2D	AUROC: 0.62 (Gaussian), 0.58 (Simplex), 0.57 (Pyramid)
Mykula 2024	DDPM	Intracranial malformations	252 2D	AUPRC = 0.79 (AnoDDPM with Simplex) and 0.80 (AutoDDPM with Gaussian)

IOU, intersection over union; 2D, two-dimensional; ACC, accuracy; Sen, sensitivity; Spe, specificity; DSC, dice similarity coefficient; AUPRC, area under precision-recall curve; AUROC, area under ROC curve

gence in fetal neurosonography remain limited. Firstly, the performance of existing models still lacks validation from large multicenter clinical studies and randomized clinical trials. Another challenge is “trust calibration”, referring to the ability of clinicians to rely on correct AI outputs while overriding them when erroneous to prevent misdiagnoses. In addition, data privacy also remains a major concern, as AI applications often involve the processing of large volumes of sensitive patient information. Finally, the substantial computational requirements and memory demands of AI models limit their feasibility in low- and middle-income regions [6,58,59]. Developing effective AI models for intracranial malformation detection demands substantial datasets, often exceeding the requirements of other AI applications. Current models predominantly rely on supervised learning, necessitating labor-intensive manual annotation of structures—a process vulnerable to variability in sonologist expertise, which may introduce labeling errors and impair model performance. Unsupervised learning techniques may offer a potential solution, while few papers make use of them. Additionally, the prognosis of intracranial malformations ranges widely, from no significant abnormalities to severe neurodevelopment delay. Diagnosis relies not solely on ultrasound findings but integrates clinical history and genetic testing.

Future research of AI models for fetal brain ultrasound requires multi-center, large-scale datasets, particularly for intracranial malformations to enhance diagnostic accuracy and broaden model applicability. Standardized algorithms are essential to guide data volume estimation and quality control. Research on fetal brain ultrasound involves various aspects, including biometric

measurements and malformation detection. Additionally, current models are unable to perform multiple tasks simultaneously. While current studies address isolated tasks, a unified multi-task model capable of simultaneous plane segmentation, biometric measurement, and malformation detection is needed. But different tasks—such as standard plane detection, and anomaly classification—may rely on distinct features. When inter-task correlations are weak or conflicting, shared representations may cause negative transfer, degrading individual task performance. Different task weighting and optimization balance may also lead to poor performance. Finally, existing diagnostic models mainly rely on three axial standard planes of the fetal brain, which is insufficient to diagnose all types of cranial malformations and may result in missed or incorrect diagnoses. MRI and US fusion technology, achieved through registration or volume navigation using either real-time or off-line ultrasound, has been shown to monitor fetal brain development and detect brain abnormalities [60,61]. Future research needs to focus on diagnostic models based on multiple imaging modalities and various planes, with the aim of improving diagnostic accuracy, reducing missed or incorrect diagnoses, and enhancing prenatal counseling and clinical decision-making.

Conclusion

AI demonstrates rapid processing and high accuracy in fetal neurosonography, showing significant clinical value as adjunctive tools. It enhances sonologists' performance in fetal brain examinations. However, the widespread clinical application of AI still needs more further study. With increase in research, this goal is likely to be achieved soon.

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Data Availability

Not applicable.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Conflict of interest

The authors have no conflict of interest to declare.

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