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# Application Progress of Artificial Intelligence in Ultrasound Diagnosis of Fetal Central Nervous System

**Xiaomei Tang**

Youjiang Medical University for Nationalities, Baise, Guangxi, China

**Abstract:** Fetal central nervous system (CNS) developmental abnormalities are common congenital malformations, and ultrasound imaging is the gold standard for prenatal assessment of fetal health. Three-dimensional (3D) ultrasound can improve the comprehensiveness of diagnostic information, but its diagnostic accuracy is highly dependent on the operator's professional experience, with a risk of missed diagnosis. Artificial intelligence (AI), especially deep learning (DL) methods, provides an important means to solve the above problems. In fetal craniocerebral ultrasound, AI mainly achieves three core applications: first, completing standard section recognition and key structure measurement, standardizing processes through algorithms, eliminating subjective deviations of operators, and promoting the transformation of fetal craniocerebral ultrasound from experience-dependent to standard-quantitative; second, assisting in malformation screening, detection, and classification diagnosis, reducing the dependence of diagnosis on doctors' experience, and narrowing the diagnostic gap between medical institutions at different levels; third, integrating multi-dimensional information to conduct risk assessment and prognosis prediction, providing quantitative basis for clinical consultation and personalized management. At present, the clinical application of AI still faces problems such as the scarcity of high-quality, large-sample, multi-center standardized ultrasound image databases, insufficient algorithm interpretability, poor compatibility with clinical systems, and unclear responsibility definition. In summary, AI has significantly improved the scientificity and reliability of fetal CNS ultrasound diagnosis. In the future, it is necessary to expand multi-center data sets and optimize algorithm performance to promote its clinical popularization and assist the precise development of prenatal medicine. This article reviews the application progress of artificial intelligence technology in ultrasound diagnosis of fetal central nervous system in recent years.

**Keywords:** Artificial Intelligence; Central Nervous System Diseases; Ultrasound; Fetus.

## 1. Introduction

The central nervous system (CNS) is composed of the brain and spinal cord, which is the most important part of the human nervous system. Fetal CNS developmental abnormalities are one of the common congenital malformations with an incidence rate of 14/10000[1]. There are many types of CNS diseases, among which neural tube defects are the most common. Domestic literature reports that its incidence rate is 1‰~2‰[2], and the prevalence rate during pregnancy is 52/100000[3]. The incidence of intracranial lesions with intact neural tubes is uncertain, because most of these intracranial lesions may not be detected at birth but only manifest later. However, long-term follow-up studies have found that the incidence of this type may be as high as 1/100[4].

Assessing the anatomical integrity of the fetal CNS is one of the most challenging tasks in prenatal ultrasound examination, because brain development and maturation are complex and orderly processes that occur at different embryonic and fetal stages[5]. Due to its real-time imaging capability, accessibility and established safety, ultrasound imaging is currently the gold standard medical imaging tool for fetal health assessment[6]. It can continuously monitor fetal development, detect abnormalities early and visualize fetal anatomical structures in detail. Compared with traditional two-dimensional (2D) technology, three-dimensional (3D) ultrasound enhances diagnostic capability by providing more comprehensive and detailed information[7, 8]. However, the accuracy and repeatability of this technology are highly dependent on the operator's professional skills and experience, and there are challenges such as operator fatigue, fetal movement and changes in maternal abdominal wall thickness, which increase the risk of missed diagnosis of CNS malformations.

Artificial intelligence (AI), especially deep learning (DL) methods, has become a transformative tool for fetal brain image analysis. The application of AI in ultrasound has shown significant clinical utility in anatomical plane detection and brain structure segmentation[9-12]. Pioneering studies have confirmed that models based on convolutional neural networks can automatically identify standard fetal craniocerebral sections and automatically measure biometric parameters such as head circumference and abdominal circumference, whose performance is close to or even surpasses that of human experts[13]. These mainly include (among others) the optimized (automatic) acquisition of standard 2D planes with correct orientation and positioning within 3DUS volumes, simplified workflow, automatic identification of key CNS and bone structures (as markers) and subsequent abnormal detection, and assessment of image quality[5].

## 2. Core Applications of AI in Fetal Craniocerebral Ultrasound

### 2.1. Standard Section Recognition and Key Structure Measurement

The primary core role of AI in fetal craniocerebral ultrasound is to solve the two core problems of standard section recognition and key structure measurement, realize the objectification and standardization of ultrasound examination through technical empowerment, and break the subjective limitations of traditional manual operations.

In terms of automatic recognition and quality assessment of standard sections, AI has the advantage of high accuracy and efficiency. Traditional ultrasound relies on the operator's experience to obtain standard sections such as lateral ventricles and transcerebellum, which is prone to affect diagnostic accuracy due to operational differences. The ScanAhead model proposed by Men et al., which adopts Swin Transformer architecture combined with probe motion assistance, predicts standard fetal head planes from scan videos and performs better than traditional 3D CNN methods in generating transventricular and transcerebellar planes[14]. The lightweight CNN attention architecture proposed by Sivasubramanian et al., with EfficientNetV2B0 as the backbone network and combined with multi-layer perceptron to realize fetal ultrasound plane classification, has a Top-1 accuracy of 96.25%, and the model parameters are only 1/40 of the traditional architecture, supporting real-time deployment on edge devices. Its GradCAM heatmap can also visualize classification basis and improve clinical interpretability[15]. The Mask R-CNN framework developed by Chen et al. can simultaneously detect lateral ventricles and calipers, automatically screen standard transventricular planes, with a section recognition accuracy of 96%, which greatly reduces deviations caused by improper scanning[16].

In the automatic segmentation and measurement of key structures, AI performs accurately and efficiently, covering core targets such as ventricular system, midline structures, posterior fossa structures and early pregnancy brain structures. For the ventricular system, the Mask R-CNN model by Chen et al., trained on 2400 images, realizes automatic measurement of lateral ventricular width through pixel-level segmentation and minimum bounding rectangle method, with an average absolute error of only 1.8mm and a measurement speed of 0.13 seconds per image[16]. The study by Ishola et al. established reference ranges for lateral ventricle-related parameters at 14-40 weeks of gestation, providing quantitative basis for standardized AI measurement[17]. For early pregnancy scenarios, Gofer et al. adopted statistical region merging (SRM) and trainable Weka segmentation (TWS) algorithms to process fetal brain images at 12-14 weeks, with the mean absolute percentage error (MAPE) of cortical measurement as low as 1.71%. Among them, the TWS algorithm shows stable segmentation performance in both normal and thickened nuchal translucency (NT) groups due to better trainability, laying a foundation for early brain abnormality screening[18]. In the assessment of midline structures and posterior fossa structures, the AI model by Sun et al. can automatically measure 10 intracranial markers such as cavum septum pellucidum and brainstem, with intraclass correlation coefficients greater than 0.75 compared with manual measurement, an average measurement time of only 0.49 seconds, and an abnormal case detection rate of 100%[19]. The ScanAhead model can accurately predict the transcerebellar plane, providing stable support for the measurement of cerebellar vermis height and other parameters[14]. The core value of AI in the screening and measurement process of standard sections is to achieve standardization through algorithms, eliminate subjective deviations and fatigue effects of operators, and provide a stable and consistent objective benchmark. Its advantages such as lightweight architecture adapting to clinical equipment, early pregnancy adaptability and improved interpretability further expand the application scenarios, promote the transformation of fetal craniocerebral ultrasound from experience-dependent to standard-quantitative, and lay a solid foundation for subsequent clinical assessment and prognosis decision-making.

## 2.2. Malformation Screening, Detection and Classification Diagnosis

In malformation screening and detection, AI models achieve accurate marking and localization of suspicious abnormal areas relying on deep learning algorithms. The craniocerebral region segmentation algorithm based on U-net network achieves a Dice coefficient of 0.942 on clinical data sets, which can efficiently extract craniocerebral structures from ultrasound images and lay a foundation for subsequent abnormal recognition[20]. The improved deep convolutional neural network combined with VGG-net can classify normal and abnormal images of two standard planes, transventricular (TV) and transcerebellar (TC), with an average F1-score of 0.96, successfully covering five common fetal brain abnormalities such as Blake's pouch cyst, Dandy-Walker malformation and ventricular dilatation[20]. Through class activation mapping (CAM) technology, AI can generate visualized heatmaps to locate lesion areas, with an average intersection over union (IOU) of 0.497. Among them, the localization accuracy of lesions such as hydrocephalus and ventricular dilatation is relatively high, providing intuitive diagnostic basis for clinical practice[20]. In addition, AI can assist in predicting open spina bifida through early pregnancy lateral ventricle biometrics, and its axial view-based assessment method is easy to operate, supplementing the screening dimension of traditional brainstem-related ratio indicators[21].

Classification and differential diagnosis are the core advantages of AI, which effectively solve the problem of distinguishing complex clinical lesions. For ventricular dilatation (VM), AI can accurately classify mild (10.0-11.9mm) and moderate (12.0-14.9mm) according to the atrial diameter of the lateral ventricle. Combined with MRI features, it can detect 5.4% of associated abnormalities missed by ultrasound, and the abnormal detection rate of moderate VM patients (60.0%) is significantly higher than that of mild VM (17.7%), mainly including ultrasound-hard-to-identify abnormalities such as supratentorial intracerebral hemorrhage and polymicrogyria[22]. In the diagnosis of corpus callosum agenesis, AI can distinguish complete and partial types through high-dimensional feature extraction. MRI combined with AI assessment shows that 6.7% of corpus callosum agenesis and 3.3% of developmental abnormalities can be accurately identified[22]. For posterior fossa cistern enlargement, AI can capture the imaging differences between Blake's pouch cyst and Dandy-Walker malformation[20]. With the help of multi-feature fusion joint spectral embedding method, it can also reveal the regional correlation between ventricular dilatation and cortical folding, providing quantitative support for etiological differentiation[23].

The clinical value of AI in fetal craniocerebral ultrasound diagnosis is mainly reflected in assisting doctors to improve diagnostic efficiency. Through standardized image analysis processes, AI reduces the dependence of diagnosis on doctors' experience, which is especially suitable for scenarios with insufficient expert resources in primary medical institutions and underdeveloped areas, helping to reduce missed diagnoses caused by insufficient anatomical cognition and outdated equipment[20]. Its high detection rate and diagnostic consistency for rare diseases effectively narrow the diagnostic gap between medical institutions at different levels[22]. In terms of visualization assistance, the lesion localization heatmaps and bounding boxes generated by AI enable 61.6% of abnormal images to achieve accurate lesion labeling, helping doctors quickly focus on key areas and improve diagnostic efficiency[24]. At the same time, AI can integrate multi-center data to establish international unified standards, such as the fetal brain structure measurement specification based on the INTERGROWTH-21st project, providing a unified reference framework for global abnormal assessment[25].

## 2.3. Risk Assessment and Prognosis Prediction

In summary, AI has significantly improved the scientificity and reliability of fetal ultrasound diagnosis through efficient abnormal recognition, accurate classification and differentiation, and intuitive diagnostic assistance. In the future, it is necessary to further expand multi-center data sets, optimize the model's ability to identify rare malformations, and promote its wide application in clinical routine screening.

In the field of fetal prenatal ultrasound assessment, the application of AI has moved from image recognition and auxiliary diagnosis to a more forward-looking prognosis prediction stage. Its core function is to solve the key problem of "how is the prognosis of fetal abnormalities", and build a quantitative assessment system by integrating multi-dimensional information, providing scientific basis for clinical consultation and personalized management, which reflects the cutting-edge application value of AI in prenatal medicine.

### 2.3.1. Prognostic Models Based on Image Features

With deep learning algorithms, AI can accurately extract features that are difficult to quantify by traditional assessment from ultrasound images, and build targeted prognosis prediction models. For fetal ventricular dilatation (VM), a common CNS abnormality, studies have found that choroid plexus volume (CPV) and related ratios are closely related to prognosis[26]. AI can automatically calculate CPV z-score. A larger CPV in fetuses with mild VM often indicates that the lateral ventricle may regress or stabilize, while a decrease in CPV in moderate to severe VM and some mild VM indicates that the condition may deteriorate, which provides a quantitative indicator for prognosis judgment[26].

The ratios of choroid plexus to lateral ventricle in early pregnancy ultrasound images are important prognostic markers. AI can accurately calculate ratios such as choroid plexus area/lateral ventricle area (PA/VA) and choroid plexus length/lateral ventricle length (PL/VL), which are significantly lower in fetuses that later develop VM than in normal fetuses[27][28]. Among them, the AUC of PA/VA ratio in predicting severe VM is 0.90, and the AUC in predicting mild VM is 0.84. The PL/VL ratio also shows good predictive efficiency, providing a powerful tool for early pregnancy risk stratification[27]. Additionally, the real-time AI system developed by Lin et al. can automatically identify standard ultrasound planes of the fetal brain (transthalamic, transventricular, transcerebellar) and key anatomical landmarks (lateral ventricles, cavum septi pellucidi, thalamus, etc.), classifying 9 intracranial anomalies including ventriculomegaly (VM). It achieves an AUC of 0.81–0.95 for diagnosing prognostically relevant intracranial pathologies, with the highest performance in VM detection, and analyzes a single plane in only 25 ms—further enriching the application of ultrasound image features in quantitative prognostic assessment of fetal anomalies[29].

### 2.3.2. Multi-Modal Data Fusion and Risk Assessment System Construction

The core trend of future AI prognosis prediction lies in the in-depth fusion of multi-modal data, breaking the limitations of a single information source. AI can integrate ultrasound image features (such as ventricular dilatation degree, cortical thickness, choroid plexus morphology), gestational age information, genetic test results (such as karyotype analysis, NIPT, CMA) and fetal brain structure standard data[25]to build a more comprehensive risk assessment model. For example, combining the choroid plexus and lateral ventricle ratios at 11-14 weeks of gestation[27][28], the severity of VM in the second trimester[26]and chromosome test results, AI can more accurately predict the neurodevelopmental outcome of fetuses after birth.

For fetuses with isolated VM, the multi-modal fusion model can integrate perinatal data (such as diagnostic gestational age, changes in ventricular width) and long-term follow-up results[30] to quantify the risk of neurodevelopmental delay corresponding to different degrees of VM—the normal development rate of mild VM is about 79%-85%, and the risk of moderate to severe developmental delay in moderate to severe VM is significantly increased[30]. In the future, with the integration of fetal MRI data, AI is expected to further improve the ability to identify subtle abnormalities of brain parenchyma, realize the full-chain prediction from structural abnormalities to functional prognosis, and provide a more three-dimensional reference for clinical decision-making.

The core value of AI in fetal prognosis assessment is to surpass the traditional qualitative diagnosis model and convert scattered medical information into quantitative prognosis probability. Through image feature mining and multi-modal data fusion, AI provides an objective and accurate tool for risk assessment of fetal abnormalities, which can not only help clinical doctors formulate personalized monitoring and intervention plans, but also provide clearer prognosis consultation for pregnant women and their families, promoting the development of prenatal medicine from abnormal discovery to precise prediction.

# 3. Supporting Conditions and Existing Challenges of AI Clinical Application

## 3.1. Data Support and Existing Shortcomings

High-quality, large-sample, multi-center standardized ultrasound image databases are the core fuel and foundation for the development of AI in the field of fetal imaging. In clinical application, the training and verification of AI models are highly dependent on unified annotation specifications and diverse data. For example, the HC18 data set includes 999 training images and 335 test images, providing key support for fetal head circumference measurement algorithms, while the FHSPs data set promotes the progress of fetal standard plane recognition technology through classification and annotation of 7129 training images and 5271 test images[31]. The value of these data sets lies not only in their scale, but also in their standardized annotation in accordance with ISUOG guidelines, ensuring the clinical relevance and consistency of the data[32]. In addition, multi-center jointly constructed databases (such as US and MRI paired data sets containing 40 cases of fetal ventricular dilatation) provide volume measurement data that lays a foundation for constructing the growth trajectory of normal and abnormal fetal brain structures[33]. The gestational age-specific brain volume reference database built based on deep learning[34], through large-sample data of 184 normal fetuses, realizes accurate screening of abnormal volumes, and its automatic segmentation algorithm takes only 6.8 seconds on average, which is highly consistent with manual measurement (Pearson r=0.996), providing a standardized volume annotation basis for AI models[34]. However, there are still significant shortcomings in current data resources: the proportion of pathological cases is low, especially the lack of annotated data on rare fetal CNS abnormalities (such as schizencephaly and lissencephaly), which limits the model's ability to identify complex cases[32]; multi-center data have equipment differences (such as ultrasound probe frequency, MRI field strength) and imaging parameter heterogeneity. Even if fusion imaging technology optimizes synchronization through multi-marker matching, it is difficult to completely eliminate the measurement deviation between the two modalities[35]; in addition, manual annotation is time-consuming and labor-intensive. For example, manual segmentation of fetal brain structures by MRI takes 25-50 minutes per case, which is difficult to meet the needs of large-scale data set construction[33].

### 3.2. Technical Bottlenecks at the Algorithm Level

Technical bottlenecks at the algorithm level still restrict the clinical transformation of AI. The "black box" attribute of the model leads to the lack of interpretability in the decision-making process. For example, although the CNN model can achieve an accuracy of more than 90% in the detection of fetal ventricular dilatation, it cannot clarify the consistency between its judgment basis and clinical diagnostic logic, which reduces the trust of clinical doctors[31]. The insufficient generalization ability of small-sample rare diseases is particularly prominent. Fetal diseases such as schizencephaly and lissencephaly have low incidence rates and insufficient annotated data, making existing models prone to false negatives in such cases[32]. At the same time, the model has poor adaptability to imaging equipment and environment. Acoustic shadows and motion artifacts of different ultrasound equipment, as well as differences in MRI scanning parameters, can significantly reduce model performance. For example, due to the influence of fetal position in late pregnancy, some volume measurements of 3D ultrasound VOCAL technology need to exclude interference data[33]; the dynamic nature of fetal development also poses challenges to algorithms. The brain structure in early pregnancy (<24 weeks) is not fully formed, resulting in a 10%-15% decrease in AI segmentation accuracy compared with late pregnancy[31]. In addition, although deep learning algorithms (such as 3D U-Net) have achieved high Dice coefficients (0.90-0.95) in fetal brain and intracranial volume segmentation, they still face technical problems such as spatial registration and consistency of feature extraction when processing multi-modal data fusion[31, 34].

### 3.3. Existing Obstacles in Clinical Integration

Multiple bottlenecks in the clinical integration process further delay the landing of AI tools. The compatibility between existing AI systems and clinical PACS systems is insufficient. Most models are difficult to achieve real-time data interaction and result feedback, requiring additional data export-import processes, which breaks the real-time workflow of ultrasound examination[31]. Although AI models specifically designed for prenatal imaging (such as the AIM-NT model for real-time NT plane recognition and measurement) have achieved a high degree of alignment with the workflow of radiologists, with a plane recognition accuracy of 88.8% and a measurement consistency (average difference of 0.03 mm) comparable to that of doctors, such targeted solutions are still rare[36]. There is no clear standard for the responsibility definition of human-machine collaboration. When AI diagnosis conflicts with doctors' judgment, the responsibility for clinical decision-making is not clear, especially in high-risk scenarios such as fetal malformation diagnosis, where legal and ethical risks cannot be ignored[31]. The strict requirements of clinical verification also constitute an important obstacle. AI models need to be verified through multi-center, large-sample prospective trials, while most current studies are limited to single-center retrospective analysis. For example, an international multi-center study on mild to moderate ventricular dilatation shows that although MRI can detect 5.4% of abnormalities missed by ultrasound, AI models have not completed prospective verification in such large-scale cohorts[22]. In addition, doctors' acceptance of AI tools is affected by operational complexity. Overly cumbersome parameter adjustment or result interpretation processes are difficult to integrate into busy clinical practice, further limiting their popularization and application[31]; at the same time, although multi-modal imaging (such as US and MRI fusion) can improve diagnostic accuracy, the high equipment cost and complex operation process also hinder its popularization in primary medical institutions[35].

## 4. Summary and Outlook

AI in the field of medical imaging is gradually realizing the transformation from an automated tool to a diagnostic assistant partner and then to a prognosis assessment tool. Its core value is always to enhance the clinical diagnostic ability of ultrasound doctors, not to replace them. Relying on technologies such as deep learning and multi-modal fusion, AI has shown accurate efficiency in automated tasks such as ultrasound image enhancement, lesion segmentation and abnormal detection. For example, the 3D U-Net model can quickly complete fetal intracranial structure segmentation and volume quantification, and fusion imaging technology can achieve synchronous and accurate measurement of MRI and ultrasound. At the diagnostic and prognostic level, AI can build a normative reference standard based on imaging data, assist in identifying pathological states, and predict disease progression and treatment response through multi-dimensional data fusion, providing important support for doctors' decision-making. In the future, it is necessary to focus on breaking through interpretable AI-related technologies to solve the current "black box" problem of models and enhance the trust of clinical doctors in AI tools; develop multi-task learning models to achieve integrated output of segmentation, diagnosis and prognosis prediction; promote the research and development of lightweight models, such as lightweight 3D CNN suitable for bedside scenarios, to meet the needs of clinical real-time diagnosis. Most existing studies are based on phantoms or single-center data. It is urgent to carry out large-scale prospective clinical studies to verify the effectiveness and stability of AI in real diagnosis and treatment scenarios; promote the transformation of AI technology from laboratory research to clinical routine tools, such as incorporating the normal standard of fetal brain volume into the prenatal ultrasound assessment process. In view of the potential risks such as data bias and privacy leakage of AI models, it is necessary to establish unified industry standards to standardize the entire process of data collection, model training and clinical application; clarify the responsibility definition of AI-assisted diagnosis to ensure the compliance and safety of technical application.

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