Real-Time Detection and Segmentation of Fetal Brain Anomalies

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***Abstract*— Fetal brain anomalies are among the most serious congenital disorders, often leading to long-term neurological and developmental challenges. Early and accurate detection is vital for effective prenatal care and intervention. Traditional diagnostic methods rely on manual interpretation of ultrasound and MRI scans, which can be time-consuming and subject to variability. In recent years, deep learning has emerged as a powerful tool in medical image analysis, offering automated, scalable, and often more consistent approaches to anomaly detection. This survey reviews recent advancements in the use of deep learning techniques for detecting fetal brain anomalies, including classification, segmentation, and detection models. Various architectures such as convolutional neural networks, autoencoders, and ensemble models are explored, along with preprocessing techniques, dataset challenges, and evaluation metrics. By comparing the strengths and limitations of different methods, this paper aims to provide a comprehensive overview of the current landscape and identify future directions for research in this critical area of prenatal diagnostics.**

***Index Terms*—Deep learning, Fetal Brain Anomalies, Medical Image Analysis, Neural Networks**

I. INTRODUCTION

Among the most important problems that can emerge during pregnancy are fetal brain abnormalities, which can frequently result in severe and lifelong neurodevelopmental disorders like cerebral palsy, epilepsy, hydrocephalus, or intellectual disability.

Early and accurate detection of congenital anomalies is not only important for appropriate medical choices but also for helping families through counseling, preparing for potential interventions, and managing perinatal care. It also saves a lot of potential threat one may have to deal with when not diagnosed right.

A. Understanding the Anomalies

Fetal neuroimaging mostly depends on two methods: ultrasound and magnetic resonance imaging (MRI) right now. While MRI offers more resolution and contrast, particularly in soft tissues, ultrasound is more commonly employed because of its real-time imaging and accessibility. Though they have advantages, both techniques usually rely on skilled radiologists or sonographers to manually interpret images—a time-consuming, observer-variable procedure that can sometimes lack sensitivity, particularly when diagnosing subtle or complex abnormalities. Fetal mobility, different gestational phases, and the innate complexity of growing brain regions add to this challenge.

B. AI Models and Feasible Capabilities

The growth of artificial intelligence (AI), especially deep learning, has created new opportunities for medical image analysis to help overcome these constraints. AI models—especially those created utilizing convolutional neural networks (CNNs), segmentation frameworks like U-Net, autoencoders, and attention-based models—have shown considerable potential in improving diagnostic accuracy and lowering the load of manual interpretation[1],[4],[6].

Increasingly used on several prenatal imaging modalities—including 2D and 3D ultrasound as well as T2-weighted MRI scans—these models can identify patterns and defects not immediately clear to the human eye.

Especially when backed by high-quality annotated datasets, supervised learning techniques have produced remarkable outcomes. Architectures such as FOAC-Net (Fetal Organ Anomaly Classification

Network) have shown how including squeeze-and-excitation blocks and naive inception modules can improve performance. While some research concentrates on brain-specific activities, others seek multi-organ defect identification, therefore expanding their possible application in prenatal diagnostics. Conversely, especially when dealing with handcrafted features or smaller datasets, conventional machine learning techniques—such as Support Vector Machines, Random Forests, and k-Nearest Neighbors—are still in use. Though easier than deep learning models, they nonetheless provide useful utility, particularly in low-resource situations[4],[6].

C. Using the Right Detection and Segmentation Methods

Apart from categorization, embryonic brain segmentation has drawn special attention. Accurate identification of crucial structures—like the cerebellum, ventricles, or corpus callosum—can provide thorough insights into fetal development. With some studies indicating encouraging outcomes managing data across numerous imaging centers and equipment kinds, researchers have investigated several deep learning-based segmentation techniques.

The increasing use of unsupervised learning is another important breakthrough in this area. Researchers are progressively looking at methods that learn patterns from normal brain development and highlight anomalies given the challenge of gathering big, annotated datasets—particularly for rare anomalies. Without needing pre-annotated problematic instances, models such as reconstruction frameworks or diffusion-based autoencoders have been utilized to spot anomalies. Some, like AutoDDPM, also include gestational age data, which helps them to find anomalies across the prenatal period[1],[3].

The use of object detection models—especially those in the YOLO (You Only Look Once) family—is a particularly thrilling path. Unlike conventional classification algorithms, YOLO can identify and pinpoint several anomalies inside a single scan in real time, hence it is well-suited for clinical use. The most recent version, YOLOv11, increases speed and accuracy even more, thus it is a good contender for real-world fetal brain abnormality detection activities.

A thorough assessment of new artificial intelligence applications in fetal brain abnormality identification is offered in this research. From conventional classifiers and deep segmentation networks to unsupervised models and real-time object detectors, it investigates a wide spectrum of approaches. The models are examined in several dimensions—including imaging modality, architectural design, learning approach, output complexity, and clinical relevance—to provide a thorough overview of the present research environment.

By means of this study, the article seeks to provide a pragmatic framework to steer future research as well as a comparative knowledge of current techniques. By making diagnosis quicker, more accurate, and more consistent, artificial intelligence has great power to transform prenatal imaging. True fulfillment of this promise, however, calls on addressing issues such dataset limitations, gestational variability, and lack of interpretability[7].

This survey underlines those shortcomings but also notes the accomplishments achieved thus far in the hopes of supporting a more intelligent, accessible, and efficient strategy to fetal brain health.

II. LITERATURE REVIEW

This section outlines the profound work we have made use to be able to understand the advancements of deep leaning, neural networks and the ever growing models and layers added to be able to achieve expected results. It also includes our findings specific to each mentioned work of research.

Lo et al.[1] presented FOAC-Net, a deep learning framework especially meant to identify fetal organ abnormalities from MRI data. The model could concentrate more effectively on both global and local features across several scales by including squeeze-and-excitation modules with naïive inception layers. FOAC-Net showed better performance than traditional models like ResNet and DenseNet trained on a dataset including normal and pathological images of the brain, spine, and heart. Although finding brain-related abnormalities was more difficult because to the intricacy of embryonic brain anatomy, the identification of spinal abnormalities was somewhat simple. The results show that in prenatal imaging jobs

incorporating multiscale feature analysis greatly improves classification accuracy.

Attallah et al.[2] Using MRI data collected from several gestational stages, suggested a thorough machine learning pipeline meant to classify a broad spectrum of fetal brain abnormalities. Based on texture and frequency domains, the approach included region-of-interest segmentation, preprocessing methods, and sophisticated feature extraction algorithms. Twenty-one machine learning models, including k-nearest neighbors and random forests, were assessed. Especially, certain models could correctly differentiate between complicated diseases as polymicrogyria and agenesis of the corpus callosum, hence exceeding 95% accuracy. This study underlines the continuing significance of traditional machine learning methods, especially when backed by careful feature engineering, in addressing high-stakes medical categorization challenges.

Shiwlani et al.[3] using specific coherent metrics emphasised on convolutional neural networks (CNNs), undertook a thorough examination of the function of deep learning in the prenatal identification of brain anomalies. The paper described how CNNs were used to automate tasks including picture segmentation, biometric measurement, and standard plane recognition. One cited study used a 16-layer CNN model that attained over 96% accuracy in telling normal from abnormal baby brain images. Though encouraging, the study underlined important shortcomings in the sector as well, such as the lack of annotated data and the urgent need for clinical and cross-validation to enable more widespread use.

Xie et al.[4] looked into deep learning's application to classify prenatal brain abnormalities in ultrasound pictures. Particularly when systems are trained on single-organ datasets, they found shared shortcomings in the area including model generalizability and data imbalance. The study team used an attention-based convolutional neural network giving priority to important anatomical areas inside the scans to solve this. While stressing the necessity of more flexible models able to identify a wider range of brain anomalies, their method showed promise in finding disorders such cerebellar hypoplasia and Dandy-Walker deformity.

Qi et al.[5] built a deep learning-based tool to find central nervous system anomalies in fetal ultrasound data. Their model was trained on a varied dataset including examples of anencephaly, encephalocele, ventriculomegaly, and holoprosencephaly. The technology improved explainability by producing heatmaps with forecasts, therefore helping doctors to understand the findings of diagnoses. Marking a significant advance toward practical and interpretable AI integration in prenatal diagnoses, the model performed consistently well throughout several gestational stages, with an accuracy of over 94%.

Mykula et al.[6] suggested a unique, using diffusion models, unsupervised anomaly identification system for fetal brain ultrasound pictures. Unlike conventional supervised techniques, their methodology did not call for annotated pathological data for training. Rather, it modeled normal anatomical distributions considering brain plane orientation and gestational age. A scalable and quantifiable option for early anomaly identification, the method showed great promise in environments with limited availability to labeled anomalous data, scoring about 80% on precision-recall.

Olsen et al.[7], using fetal brain ultrasound data, proposed a reconstruction-based technique for abnormality diagnosis. Trained just on photographs of normal anatomy, their model knew to rebuild healthy embryonic brain structures. Deviations from these reconstructions were noted as possible abnormalities. The technique offered a new and understandable way to find rare or slight abnormalities without depending on labeled abnormal cases, doing well in clinical tests.

Lad et al.[8] was aiming at identifying ten important fetal brain areas from ultrasound pictures, offered a segmentation technique. The model showed great generalizability and strong performance across several ultrasound systems and clinical environments by improving a U-Net architecture with inception modules and using customised data augmentation methods for prenatal imaging. Their results highlight the possibility of using deep learning algorithms in actual prenatal care settings, where informed diagnosis and monitoring depend on consistent and dependable segmentation processes followed throughout.

III. RESEARCH GAP

Although every single paper in the literature offers different methods, ideas, and contributions to fetal brain abnormality diagnosis, a closer reading uncovers a collection of repeating patterns and cross-cutting issues that go beyond technical distinctions. These reoccurring motifs highlight not only the increasing complexity of artificial intelligence model creation but also the more general systematic problems forming how these technologies are created, validated, and finally deployed in clinical practice.

Throughout the body of reviewed work, particular questions keep coming up—questions that address the limitations of present datasets, the scalability of suggested models, the need for gestational sensitivity in algorithm design, and the degree to which these solutions are created with real-world clinical use in mind. These are not limited concepts.

This survey does not intend to assess individual studies in isolation; rather, it hopes to combine their aggregate insights to find general trends, systematic limitations, and significant chances for progress.

Drawing links between various studies helps one to go beyond model-centric comparisons and toward a more comprehensive knowledge of how the subject is developing—and where it is still lacking.

These findings are summarized in Table 1. It summarizes how every study adds to or ignores these vital points by means of a brief overview and it catches the fundamental topics of attention that arose during the literature evaluation.

The table shows both the maturity and limits of present research efforts from data scarcity and variability in gestational development to the interpretability of artificial intelligence output and the degree of clinical preparedness.

These ideas taken together provide the basis for the following parts of this report. They promote the evolution of AI systems toward safer, more robust, and clinically relevant solutions in prenatal neuroimaging.

Not only at the algorithmic level but also in the development of frameworks supporting reproducibility, external validation, and ethical deployment becomes increasingly crucial as the area develops.

TABLE I

RESEARCH INFERENCE

Serial Number	Core Challenge	Implication For Fetal Brain Anomaly Detection Research
1	Data Scarcity	Expert-labeled datasets are limited, especially for rare anomalies. This motivates the exploration of unsupervised learning, weak supervision, or transfer learning to reduce reliance on exhaustive annotation.
2	Architectural Progression	There's a shift from conventional CNNs to more specialized architectures like attention networks and diffusion models, enabling better handling of anatomical complexity and image variability. This trend supports the need for task-adaptive and anatomically aware designs in fetal brain detection.
3	Task-Modality Optimization Gap	Many models are either modality-specific or task-isolated (e.g., classification vs. segmentation), lacking generalizability. The field needs cross-compatible architectures that align the imaging modality (MRI vs. ultrasound) with task objectives (detection, segmentation, anomaly scoring).
4	Lack of Gestational Robustness	Most models are not designed to handle anatomical changes across gestational stages. Addressing this limitation with gestational-age–adaptive models is crucial for accurate longitudinal fetal monitoring.
5	Clinical Integration Limitations	Despite strong experimental results, many models lack interpretability, clinician trust, and multi-center validation. Future systems must prioritize explainability, real-time performance, and generalizability across devices and populations.

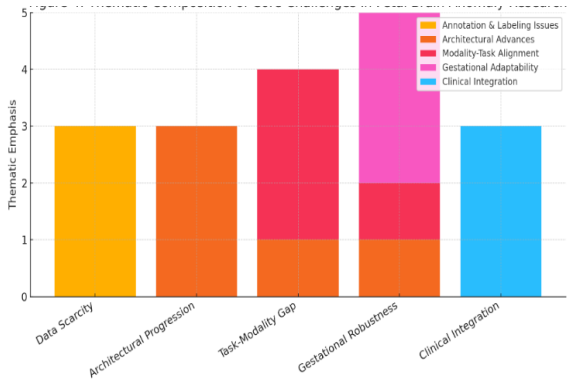

Fig. 1 Challenges In Fetal Brain Anomaly Research

The stacked bar chart in Fig. 1 visually shows how each main difficulty in the discipline relies on different subthemes across the examined literature. Each bar is divided down into smaller theme contributions corresponding to a core problem—such as data scarcity or clinical integration—annotation concerns, architectural changes, or adaptability to gestational age as depicted and multiple colours.

The goal is to show how many every difficulty is. For instance, "Task-Modality Gap" draws on architectural innovation and the requirement for cross-compatible models, while "Gestational Robustness" reveals close connections to both modality alignment and architecture, stressing the need of creating systems that fit fetal development phases. "Clinical Integration" emphasizes actual world preparedness elements including scientific validation, results, functions and explainability.

IV. THEMATIC LEARNINGS AND FINDINGS

This part addresses the main conceptual concepts that came out throughout the literature research process following the cross-paper analysis shown in Table 1. These observations emphasize more general consequences across datasets, architectures, therapeutic expectations, and research orientation rather than specific to individual methods.

A. Modality Focus: With limited crossover, most models are created exclusively for either MRI or ultrasound. While it has increased performance inside each modality, it restricts their generalizability. Some modern methods are beginning to investigate cross-modal training and transferable characteristics, which might increase clinical application flexibility as shown in Figure 2. below.

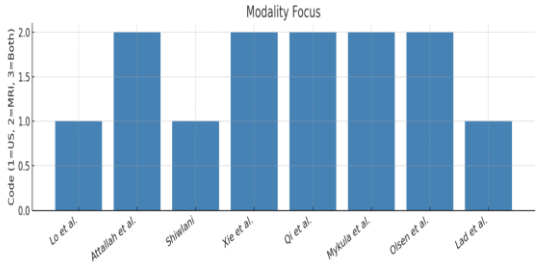

Fig. 2 Modality Focus

B. Output Scope: While early work focused on simple classification, newer models are beginning to offer more informative outputs — including segmentation maps and condition-specific predictions. This shift brings models closer to what clinicians actually need during diagnosis and follow-up as represented in Figure 3 below.

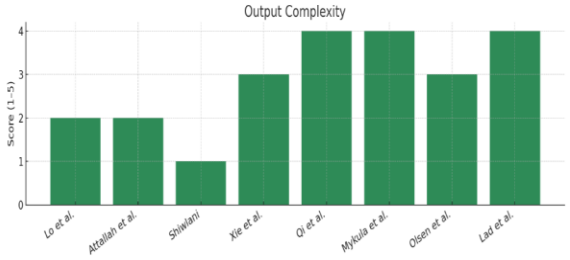

Fig. 3 Output Complexity

C. Gestational Adaptation: Fetal brain development changes significantly across gestation, yet many models do not account for age-specific anatomical differences. A few recent studies have introduced age-aware designs or datasets spanning different gestational weeks, marking a step toward more adaptive solutions as in figure 4.

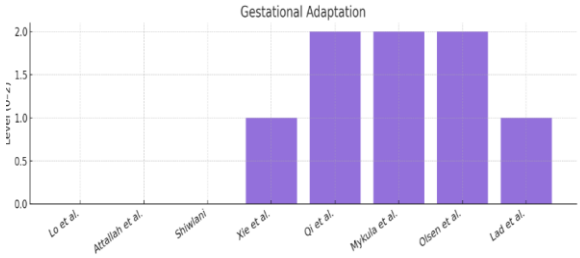

Fig. 4 Gestational Period

D. Clinical Readiness: Interpretability, speed, and validation across different settings are still limited but improving. More models now include visual explanation tools and multi-site testing, which are

important steps toward real-world clinical integration as in Figure 5.

Fig. 5 Clinical Readiness

E. Data-Efficient Learning Process: Unsupervised and generative approaches are gaining traction, particularly where annotated data is limited. Models trained on normal scans to detect deviations are proving effective, offering a scalable path for rare anomaly detection with less labeling effort as in Figure 6 below.

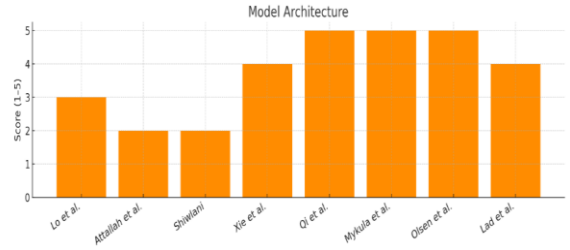

Fig. 6 Model Architecture

Several research point to a balanced emphasis on different elements, suggesting a holistic approach to model building that includes both technical efficacy and therapeutic relevance. These works include creative model designs and thoughts for practical deployment, including interpretability and incorporation into clinical workflows, hence complementing more general translational goals.

By contrast, many research show a more focused approach, sometimes giving either basic machine learning techniques or assessments depending on certain modalities top priority. Though methodologically sound and offering vital foundation, these works might not sufficiently handle the larger issues connected to fetal brain imaging, such anatomical variation throughout gestational stages and clinical operational usefulness and reliability. Especially those enabling detection, segmentation, and classification inside integrated systems, the graph shows a notable trend of increasing investment in architectural complexity and enhanced output mechanisms. One field that has not been much researched is gestational adaptation. A key yet underappreciated topic in modern studies is the ability of models to generalize across different phases of fetal development. This finding suggests a need for models guaranteeing durability across the pregnancy timeline and including developmental context.

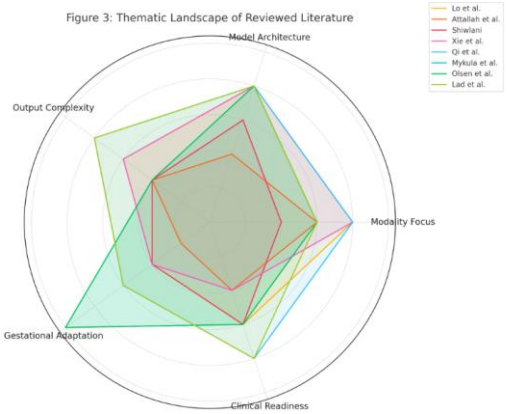

Fig. 7 Chart to Analyse the Five Thematic Learnings

Thematic distribution of current research in fetal brain abnormality detection over five main dimensions—modality focus, architectural innovation, output complexity, gestational adaptability, and clinical readiness—is shown in Figure 7. The visual depiction shows the varying degrees of focus given to different aspects in the conducted study focusing on multiple aspects involved to be able to come up with definitive inferences.

V. CONCLUSION

This survey presents a comprehensive overview of recent advancements in the application of artificial intelligence for fetal brain anomaly detection, drawing insights from a diverse range of machine learning and deep learning methodologies. The reviewed studies highlight notable progress in tasks such as classification [1], [2], segmentation [8], and unsupervised anomaly detection [6], [7], applied across various imaging modalities including ultrasound [4], [5], [8] and MRI [1], [2]. From traditional models enhanced through handcrafted features [2] to more sophisticated deep architectures like FOAC-Net [1], attention-based CNNs [4], and YOLO-style detectors [5], the field continues to evolve toward greater diagnostic accuracy and efficiency.

Despite these technological advancements, several persistent challenges are evident across the literature. Data scarcity and gestational variability remain significant obstacles to model generalizability and robustness [3], [6]. The lack of standardized, large-scale datasets and limited external validation of model performance hinder the translation of AI systems into clinical environments. Moreover, while several approaches aim to improve explainability through heatmaps or visual outputs [5], a broader concern exists regarding the interpretability and transparency of these models in real-world decision-making contexts [3].

Future work must prioritize the development of clinically integrated, gestationally adaptable models capable of functioning across varied patient populations and imaging setups [6], [7]. Emphasis should be placed on interdisciplinary collaboration, particularly between data scientists and clinical practitioners, to ensure that algorithmic innovations are aligned with practical diagnostic workflows. With continued research and responsible implementation, AI has the potential to become a valuable aid in prenatal neuroimaging—enabling earlier, more accurate, and more equitable detection of fetal brain anomalies.

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