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Review

Advancements in Artificial Intelligence for Fetal Neurosonography: A Comprehensive Review

Jan Weichert [1,2,*] and Jann Lennard Scharf [1]

[1] University Hospital of Schleswig-Holstein, Department of Gynecology and Obstetrics, Division of Prenatal Medicine, Ratzeburger Allee 160, 23538 Luebeck, Germany
[2] Elbe Center of Prenatal Medicine and Human Genetics, Willy-Brandt-Str. 1, 20457 Hamburg
* Correspondence: jan.weichert@uksh.de; Tel.: +49 451 500 41770

Abstract: Detailed sonographic assessment of the fetal neuroanatomy plays a crucial role in prenatal diagnosis, providing valuable insights into timely well-coordinated fetal brain development and detecting even subtle anomalies that may impact neurodevelopmental outcomes. With recent advancements in artificial intelligence (AI) in general and medical imaging in particular, there has been growing interest in leveraging AI techniques to enhance the accuracy, efficiency, and clinical utility of fetal neurosonography. The paramount objective of this scoping review is to discuss the latest developments in AI applications in this field, focusing on image analysis, automation of measurements, prediction models for neurodevelopmental outcomes, visualization techniques, and integration into clinical routine.

Keywords: fetal; ultrasound; prenatal; artificial intelligence; neurosonography; machine learning; convolutional neural networks

1. Introduction

The Assessment of the anatomic integrity of the fetal central nervous system (CNS) is one of the most challenging tasks during prenatal sonographic work-up as brain development and maturation constitutes a complex and well-orchestrated process at various embryonic and fetal stages. To preclude diagnostic errors, national and international guidelines explicitly paid attention to the fact that the appearance of the brain underlies profound changes throughout gestation. Although brain anomalies are among of the most common fetal malformations with an estimated prevalence of 9.8-14 per 10.000 live births [1,2], their in utero perception fundamentally requires familiarity with sonographic brain anatomy, artifacts and a designated vigilance for the necessity of subsequent targeted multiplanar assessment of the entire fetal CNS (neurosonography) [3,4]. In general, the efficacy of ultrasound (US) screenings largely hinges on the operator's skill in navigating to and reproducing standard imaging planes and this, in turn strongly relates to the gestational age (GA) at examination. In this context, it could be noticed that in the recent past the majority of severe congenital brain anomalies were readily identified prenatally by applying a systematic, protocol-based US survey [5,6]. Nevertheless, detection rates of fetal brain lesions in an unselected population remain somewhat unsatisfactory and more subtle changes might escape an early diagnosis. In part, this might be explained by the fact that even though advanced technologies as three-dimensional US (3DUS) undoubtedly have the potential to contribute to an improved detailed CNS evaluation, there is still little consensus as to the ideal method of volume acquisition, settings, and analysis of the volume and an overall lack in standardization of volumetric assessment [7]. On the other hand, DiMascio et al. stated in their systematic review that fetal brain charts substantially suffer from poor methodology and are at high risk of biases, mostly when focusing on relevant neurosonographic issues [8]. In addition, another publication demonstrated that fetal cortical brain development in fetuses conceived by assisted reproductive technology seems to be different from those conceived spontaneously, as expressed by a reduced sulci depth [9]. This underpins the complexity of an all-encompassing thorough assessment of the fetal brain. Beyond any doubt, prenatal US is capable of

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providing precise information regarding fetal anatomical integrity and the severity of abnormal conditions derived from high-quality images with increased diagnostic accuracy and reliability. The transabdominal route remains the technique of choice for comprehensive anatomic evaluation of dedicated organs like the fetal brain. This clearly demonstrates that the currently available image data source has to deal with a combination of maternal, fetal, technical, environmental, and acoustic factors hampering image clarity, data acquisition and eventually establishing precise antenatal diagnoses.

Current research approaches regarding the clinical applicability of artificial intelligence (AI)-assisted methods in the context of fetal neurosonography (beyond the first trimester) are heterogeneous and, with few exceptions, software solutions being of use for clinical routine are rather rare. However, several promising research topics in this field has emerged. These mainly include (among others) optimized (automated) acquisition of 2D standard planes with correct orientation and localization within a 3DUS volume, a simplified workflow, automated recognition of crucial CNS and bony structures (as landmarks) with subsequent detection of anomalies, evaluation of image quality and assessment of GA by evaluating neurodevelopmental maturation [10–14].

This review aims to summarize current knowledge about potential diagnostic targets for AI algorithms in assessment of the fetal brain in a clinical context and highlights why AI applications are increasingly being integrated into prenatal US interrogation and illuminate their practical added value.

2. AI in Prenatal Diagnosis

The In the very recent past, we are witnessing the tidal wave of artificial intelligence and their computational applications in healthcare in general and in medical image analysis in particular. In 2022, Dhombres et al. published a systematic review regarding the actual contributions of AI reported in obstetrics and gynecology (OB/GYN) discipline journals. In detail, most articles covered method/algorithm development (53%, 35/66), hypothesis generation (42%, 28/66), or software development (3%, 2/66). Validation was performed on one data set (86%, 57/66), while no external validation was reported [15].

Machine learning (ML) is a powerful set of computational tools that learn from large (structured) data sets and trains models on descriptive patterns and subsequently applies the knowledge acquired to solve the same task in new situations. Although ML algorithms are presently widely deployed in medicine expanding diagnostic and clinical tools to augment iterative, time-consuming and resource-intensive processes and streamline workflows, considerable human supervision is needed. AI models that use Deep learning architectures (DL; a subdomain of ML) which predominantly leverage large-scale neural networks mimicking silicon circuit synapses tend to outperform traditional machine learning methods in complex tasks and constitute the most suitable methodology for image analysis. Based on a detailed scoping review dealing with the most-cited papers using DL in literature from 2015 to 2021, the number of surveyed publications for segmentation, detection, classification, registration, and characterization tasks comprised 30, 20, 30, 10, and 10 percent, respectively [16]. It is of note that the quality of obstetric US screening images is crucial for clinical downstream tasks, involving assessment of fetal growth and development, in utero compromising, prediction of preterm birth and detection of fetal anomalies, respectively. It is now widely recognized by leading US equipment manufacturers and most of the experts in this field, that there are clear benefits of utilizing AI technologies for US imaging in prenatal diagnostics. A multitude of Convolutional Neural Network (CNN)-based AI applications in US imaging have showcased that AI models can achieve comparable performance to clinicians in obtaining appropriate diagnostic image planes, apply appropriate fetal biometric measurements, and accurately assessing abnormal fetal conditions [10-13,17,18].

As accurate head measurements are of crucial importance in prenatal and obstetrical ultrasound surveillance, a plethora of automatic methods for fetal head analysis have been proposed. Most studies focused preferentially on size and shape of the bony skull - excluding internal structures - while applying solely head detection methods (e. g. object (skull) detection using bounding boxes,

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segmentation methods ± ellipse fitting, edge-based and contour-based methods). Torres et al. published an excellent comprehensive state-of-the-art review tabulating more than 100 published papers on computational methods for fetal head, brain and standard plane analysis in US images [13]. Moreover, the survey also summarized image enhancement protocols of US images, including methods that find the fetal head aligned to a coordinate system, compounding approaches, as well as US and multimodal registration methods. The authors provided an exhaustive analysis of each method based on its clinical application and theoretical approach and in their concluding remarks they stated - despite the fact that a multitude of distinct image processing methods has been developed in the recent past (which mainly comprised deep learning approaches) - there is a need for new architectures to boost the performance of these methods. A strong database is seen as an indispensable prerequisite, which reinforces the need for public US benchmarks and for the development of approaches that deal with limited data (e.g., transfer learning approaches). And on the other hand, more effort should be made in AI research for the development of methods to segment the head in 3D images as well as methods to reliable detect abnormalities or (even subtle) lesions within the fetal brain. Accordingly, Ramirez Zegarra and Ghi suggested an ideal AI setting which clearly addresses the urgent need for more multitasking DL models that are trained for both the detection of fetal standard planes, identification of fetal anatomical structures and performance of automatic measurements that in turn will consequently be able to generate alarm messages in the event of malformations [19].

In fact, in the last decade several AI-related scientific studies have been conducted to improve the quality of prenatal diagnoses by focusing on three major issues: (I) detection of anomalies, fetal measurements, scanning planes, and heartbeat, (II) segmentation of fetal anatomic structures in US still frames and videos and (III) classification of fetal standard diagnostic planes, congenital anomalies, biometric measures, and fetal facial expressions [20].

Various researchers were able to develop algorithms that were able to reproducibly quantify biometric parameters with high accuracy. Some of them will be discussed critically below. On the other hand, quite a number of AI models were trained with inadequate and/or insufficiently labeled samples, which led to overfitting problems and performance degradation [14]. 'All models are wrong, but some are useful', an aphorism on the subject of statistics more than 50 years ago coined by George E.P. Box, that describes the general dilemma in the targeted application of computational modeling approaches and AI solutions (not only in the past) [21].3. Results

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3. AI in Fetal Neurosonography

Adopting experiences made with automated techniques in fetal cardiac assessment, further refinements in AI algorithms or development of anomaly-specific learning algorithms could help achieve more granular detections of unique CNS lesions [22]. This has the potential to risk stratify certain fetal populations. But, as a matter of fact, it has to be acknowledged that algorithms developed for fetal imaging recognition require a larger database compared with other AI algorithms, due to the similar appearance of the different US planes [19]. However, it should be noted that currently available and clinically approved approaches for the extensive processing of three-dimensional data sets of the fetal CNS do only sparsely exploit the diagnostic potential of volume US. In fact, it is currently not feasible to perform both simple and more complex tasks such as assessment of the total brain volume, rendering of the brain surface, slicing and display of all diagnostic sectional planes (in accordance with the ISUOG guidelines) in addition to multiplanar image display on one and the same 3D volume (vendor-independent). This applies to both conventional tools and AI frameworks and does not appear to be readily explainable in the light of the existing scientific literature with generally highly complex AI pipelines. In this regard, developers and engineers on the one hand and clinicians on the other should work together more intensively to find relevant integrative volume-based solutions for clinical routine as quickly as possible.

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In 2023 an international research group developed a normative digital atlas of fetal brain maturation based on a prospective international cohort (INTERGROWTH-21st Project) using more than 2,500 serially acquired 3D fetal brain volumes [23]. In preparation of this fully-functional digital brain atlas, the authors proposed an end-to-end, multi-task CNN that both extracts and aligns the fetal brain from original 3D US scans with a high degree of accuracy and reliability (Brain Extraction and Alignment Network; BEAN) [24–26]. These obligate steps were mandatory (as in most neuroimage analysis pipelines) to enhance the visibility of brain structures within the 3D US templates and on the other hand to significantly reduce the amount of processed extra-cranial volume information and lastly to overcome the positional variation of the brain inside the scan volume. From the author's perspective, there is no doubt that introduction of computerized human body atlases either based on US or MRI image data (as published earlier by Gholinpour et al. [27]) will contribute to our understanding of fetal developmental processes in general and brain maturation in particular by providing rich contextual information of the inherently 3D (CNS) anatomy.

The clinical applicability of semiautomatic volumetric approaches in terms of a detailed reconstruction of diagnostic planes of the fetal brain has been validated in previous studies [28–30]. Very recently a 3D UNet-based network for 3D segmentation of the entire CNS using an intelligent navigation to locate CNS planes within the 3D volume has been introduced (fully automated 5DCNS+™). While applying this tool, our group was able to show that CNS volume data sets (acquisition originated from an axial transthalamic plane) could readily be reconstructed into a nine-view template in less than 12 seconds on average facilitating the generation of a complete neurosonogram with high accuracy, efficiency and reduced operator-dependency, confirming previous findings, accordingly (data not shown).

Lu et al. reported on an automated software (Smart ICV™) to total fetal brain volume retrieved from 3DUS volume data. This novel technique showed a high intra- as well as inter-observer intra-class coefficient (0.996 and 0.995, respectively) and high degree of reliability compared with a manual approach using Virtual Organ Computer-aided AnaLysis (VOCAL™) [31]. An overview of current Ai-driven algorithms with either clinical or pre-clinical context is given in Table 1.

DL algorithms have become the methodology of choice for imaging analysis [16,18,32,33]. DL models are capable of overcoming US image-related challenges including inhomogeneities, (shadowing) artifacts, poor contrast and intra- and inter-clinician acquisition and measurement variability, respectively. Fiorentino and co-workers categorized published work in the field of fetal US image analysis applying a plethora of different DL algorithms. Their review surveyed more than 150 research papers to elaborate the most investigated tasks addressed using DL in this field [18]. The authors could demonstrate that fetal standard-plane (SP) detection (19.6%) and fetal-biometry estimation (20.9%) were among the most prevalent tasks. Fetal CNS and heart were the most explored structures in standard plane detection while fetal head circumference was the most frequently investigated measurement in biometry estimation. In 49 % researchers trained DL pipelines for anatomical structure analysis. The most studied anatomical structures were heart and brain, contributing with 26.7% and 20.0% of the surveyed papers, respectively. In case of the latter, the analysis is performed both with 2D and, more recently, 3D images to assess brain development and localization, structure segmentation and GA estimation. Challenges to be addressed regarding AI in image analysis in general comprise: limited availability of (multi-expert) image annotation, limited robustness of DL algorithms due to the lack of large training data sets (interestingly only a minority of DL studies use data from routine clinical care), inconsistent use of both performance metrics and testing datasets hampering a fair comparison between different algorithms and research proposing semi-, weakly or self-supervised approaches is still scarce [10,18,32].

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Table 1. Neurosonographic Studies related to artificial intelligence.

Reference, year	country	GA (wks)	study size (n)*	data source	type of method	purpose /target	task	Description of AI	clinical value***
Rizzo *et al.*, 2016 [34]	I	21 (mean)	120	3D	n. s.	SFHP (axial) biometry	automated recognition of axial planes from 3D volumes	5D CNS software	++
Rizzo *et al.*, 2016 [35]**	I	18-24	183	3D	n. s.	SFHP (axial/ sagittal/coronal) biometry	evaluation of efficacy in recon- structing CNS planes in healthy and abnormal fetuses	5D CNS+ software	+++
Ambroise-Grandjean *et al.*, 2018 [36]	F	17-30	30	3D	n. s.	SFHP (axial) biometry (TT, TC)	automated identification of axial from 3DUS and to measurement BPD and HC	SmartPlanes CNS	++
Welp *et al.*, 2020 [30]**	D	15-36	1.110	3D	n. s.	SFHP (axial/ sagittal/coronal) biometry	validating of a volumetric approach for the detailed assessment of the fetal brain	5D CNS+ software	+++
Pluym *et al.*, 2021 [37]	USA	18-22	143	3D	n. s.	SFHP (axial) biometry	evaluation of accuracy of automated 3DUS for fetal intracranial measurements	SonoCNS software	++
Welp *et al.*, 2022 [29]**	D	16-35	91	3D	n. s.	SFHP/anomalies biometry	evaluation of accuracy and reliability of a	5D CNS+ software	+++

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							volumetric approach in abnormal CNS		
Gembicki *et al.*, 2023 [28]**	D	18-36	129	3D	n. s.	SFHP (axial/ sagittal/coronal) biometry	evaluation of accuracy and efficacy of AI-assisted biometric measurements of the fetal CNS	5D CNS+ software, SonoCNS software	++
Han *et al.*, 2024 [38]	CHN	18-42	642	2D	DL	Biometry (incl. HC, BPD, FOD, CER, CM, Vp)	automated measurement and quality assessment of nine biometric parameters	CUPID software	++
Yaqub *et al.*, 2012 [39]	UK	19-24	30	3D	ML	multi-structure detection	localization of four local brain structures in 3D US images	Random Forest Classifier	++
Cuingnet *et al.*, 2013 [40]	UK	19-24	78 volumes	3D	ML	SFHP	fully automatic method to de- tect & align fetal heads in 3DUS	Random Forest Classifier, Template deformation	++
Sofka *et al.*, 2014 [41]	CZ	16-35	2089 volumes	3D	ML	SFHP	automatic detection and measurement of structures in CNS volumes	Integrated Detection Network (IDN)/FNN	+
Namburete *et al.*, 2015 [42]	UK	18-34	187	3D	ML	sulcation/gyration	GA prediction	Regression Forest Classifier	++

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Yaqub *et al.*, 2015 [43]	UK	19-24	40	3D	ML	SFHP	extraction & categorization unlabeled fetal US images	Random Forest Classifier	+
Baumgartner *et al.*, 2016 [44]	UK	18-22	201	2D	DL	SFHP (TT, TC)	retrieval of standard planes, saliency maps to extract bounding boxes of CNS anatomy	CNN	+++
Sridar *et al.*, 2016 [45]	IND	18-20	85	2D	DL	structure detection	image classification & structure localization in US images	CNN	+
Yaqub *et al.*, 2017 [46]	UK	19-24	40	3D	DL	SFHP, CNS anomalies	localization of CNS, structure detection, pattern learning	Random Forest Classifier	+
Qu *et al.*, 2017 [47]	CHN	16-34	155	2D	DL	SFHP	automated recognition of six standard CNS planes	CNN, Domain Transfer Learning	++
Namburete *et al.*, 2018 [25]	UK	18-34	739 images	2D/3D	DL	structure detection	3D brain localization, structural segmentation and alignment	multi-task CNN	++
Huang *et al.*, 2018 [48]	CHN	20-29	285	3D	DL	multi-structure detection	detection of CNS structures in 3DUS & measurement CER/CM	VP-Net	++
Huang *et al.*, 2018 [49]	UK	20-30	339 images	2D	DL	structure detection (CC/CP)	to standardize intracranial anatomy & measurements	Region descriptor, Boosting classifier	++

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van den Heuvel *et al.*, 2018 [50]	NL	10-40	1.334 images	2D	ML	biometry (HC)	automated measurement of fetal head circumference	Random Forest Classifier Hough transform	+
Dou *et al.*, 2019 [51]	CHN	19-31	430 volumes	3D	ML	SFHP/structure detection	automated localization of fetal brain standard planes in 3DUS	Reinforcement learning	++
Sahli *et al.*, 2019 [52]	TUN	n/a	86	2D	ML	SFHP	automated extraction of biometric measurements and classification normal/abnormal	SVM Classifier	++
Alansary *et al.*, 2019 [53]	UK	n/a	72	3D	ML/DL	SFHP/structure detection	localization of target landmarks in medical scans	Reinforcement learning deep Q-Net	+
Lin *et al.*, 2019 [54]	CHN	14-28	1.771 images	2D	DL	SFHP/structure detection	automated localization of six landmarks & quality assessment	MF R-CNN	+
Bastiaansen *et al.*, 2020 [55]	NL	1st trimester	30	2D/3D	DL	SFHP (TT)	fully automated spatial alignment and segmentation of embryonic brains in 3D US	CNN	+
Xu *et al.*, 2020 [56]	CHN	2nd/3rd trimester	3.000 images	2D	DL	SFHP	simulation of realistic 3rd- from 2nd-trimester images	Cycle-GAN	++

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Ramos *et al.*, 2020 [57]	MEX	n/a	78 images	2D	DL	SFHP biometry (TC) GA prediction	detection and localization of cerebellum in US images, biometry for GA prediction	YOLO	+
Maraci *et al.*, 2020 [58]	UK	2nd trim	8.736 images	2D	DL	biometry (TC) GA prediction	estimation of GA through automatic detection and measurement of the TCD	CNN	+
Chen *et al.*, 2020 [59]	CHN	n/a	2.900 images	2D	DL	SFHP biometry (TV)	to demonstrate the superior performance of DL pipeline over manual measurement	Mask R-CNN ResNet50	+
Xie *et al.*, 2020 [60]	CHN	18-32	92.748	2D	DL	SFHP (TV, TC) CNS anomalies	image classification as normal or abnormal, segmentation of craniocerebral regions	U-Net VGG-Net	++
Xie *et al.*, 2020 [61]	CHN	22-26	12.780	2D	DL	SFHP, CNS anomalies	binary image classification as normal or abnormal in standard axial planes	CNN	++
Zeng *et al.*, 2021 [62]	CHN	n/a	1.354 images	2D	DL	biometry	image segmentation for automatic HC biometry	DAG V-Net	+

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Burgos Artizzu *et al.*, 2021 [63]	ESP	16-42	12.400 images (6.041 CNS)	2D	DL/ML	SFHP	evaluation of the maturity of current DL classification tested in a real clinical environment	19 different CNNs MC Boosting algorithm HOG classifier	++
Gofer *et al.*, 2021 [64]	IL	12-14	80 images	2D	ML	SFHP/structure detection (CP)	classification 1st trimester CNS US images and earlier diagnosis of fetal brain abnormalities	Statistical Region Merging Trainable Weka Segmentation	+
Skelton *et al.*, 2021 [65]	UK	20-32	48	2D/3D	DL	SFHP	assessment of image quality of CNS planes automatically extracted from 3D volumes	Iterative Transformation Network (ITN)	++
Fiorentino *et al.*, 2021 []	I	10-40	1.334 images	2D	DL	biometry (HC)	head localization and centering	multi-task CNN	++
Yeung *et al.*, 2021 [66]	UK	18-22	65 volumes	2D/3D	DL	SFHP/structure detection	mapping 2D US images into 3D space with minimal annotation	CNN	
Montero *et al.*, 2021 [67]	ESP	18-40	8.747 images	2D	DL	SFHP	generation of synthetic US images via GANs and to improve SFHP classification	Style-GAN	++
Moccia *et al.*, 2021 [68]	I	10-40	1.334 images	2D	DL	biometry (HC)	fully automated method to HC delineation	Mask-R2CNN	+

Wyburd *et al.*, 2021 [69]	UK	19-30	811 images	3D	DL	structure detection/ GA prediction	automated method to predict GA by cortical development	VGG-Net ResNet-18 ResNet-10	++
Shu *et al.*, 2022 [70]	CHN	18-26	959 images	2D	DL	SFHP (TC)	automated segmentation of the cerebellum, comparison with other algorithms	ECAU-Net	+
Hesse *et al.*, 2022 [71]	UK	18-26	278 images	3D	DL	structure detection	automated segmentation of four CNS landmarks	CNN	+++
Di Vece *et al.*, 2022 [72]	UK	20-25	6 volumes	2D	DL	SFHP/structure detection	estimation of the 6D pose of arbitrarily oriented US planes	ResNet-18	++
Lin *et al.*, 2022 [73]	CHN	18-40	16.297/166	2D	DL	structure detection	detection of different patterns of CNS anomalies in standard planes	PAICS YOLOv3	+++
Sreelakshmy *et al.*, 2022 [74]‡	IND	18-20	740 images	2D	DL	biometry (TC)	segmentation the cerebellum from fetal brain images	ResU-Net	-
Yu *et al.*, 2022 [56]	CHN	n/a	3.200 images	2D/3D	DL	SFHP	automated generation of coronal and sagittal SPs from axial planes derived from 3DVol	RL-Net	++

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Alzubaidi *et al.*, 2022 [75]	QTAR	18-40	551	2D	DL	biometry (HC)	GA and EFW prediction based on fetal head images	CNN, Ensemble Transfer Learning	++
Coronado-Gutiérrez *et al.*, 2023 [76]	ESP	18-24	12.400 images	2D	DL	SFHP, multi-structure delineation	automated measurement of brain structures	DeepLab CNNs	++
Ghabri *et al.*, 2023 [20]	TN	n/a	896	2D	DL	SFHP	to classify fetal planes/Accurate fetal organ classification	CNN: DenseNet169	++
Lin *et al.*, 2023 [77]	CHN	n/a	558 (709 (images/videos)	2D	DL	SFHP	improved detection efficacy of fetal intracranial malformations	PAICS YOLO	+++
Rauf *et al.*, 2023 [78]	PK	n.s.	n.s.	2D	DL	SFHP	Bayesian optimization for the classification of brain and common maternal fetal ultrasound planes	Bottleneck residual CNN	+
Alzubaidi *et al.*, 2023 [79]	QTAR	18-40	3.832 images	2D	DL	SFHP	Evaluation of a Large-scale annotation dataset for head biometry in US images	Multi-task CNN	+
Alzubaidi *et al.*, 2024 [80]	QTAR	18-40	3.832 images (20,692 images)	2D	DL	biometry	advanced segmentation techniques for head biometrics	FetSAM Prompt-based Learning	+

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							in US imagery		
Di Vece *et al.*, 2024 [81]	UK	20-25	6 volumes	2D/3D	DL	SFHP (TV)	detection & segmentation of the brain; plane pose regression; measurement of proximity to target SP	ResNet-18	++
Yeung *et al.*, 2024 [82]	UK	19-21	128.256 images	2D	DL	SFHP	reconstruction of brain volumes from freehand 2D US sequences	PlaneInVol ImplicitVol	++
Dubey *et al.*, 2024 [83]	IND	10-40	1.334 images	2D	DL	biometry (HC)	Automated head segmentation and HC measurement	DR-ASPnet, Robust Ellipse Fitting	++

Clinically validated (and commercially available) software in grey shaded rows. Abbreviations: 2D, two dimensional; 3D, three dimensional; BPD, biparietal diameter; CER, cerebellum; CNN, convolutional neural network; CNS, central nervous system; CP, choroid plexus; CSP, cavum septum pellucidum; DL, deep learning; FOD, frontooccipital diameter; GA, gestational age; GAN, generative adversarial network; HC, head circumference; LV, lateral ventricles; n/a, not applicable; n. s., not specified; PAICS, prenatal ultrasound diagnosis artificial intelligence conduct system; ResNet, residual neural network; SFHP, standard fetal head plane; SVM, support vector machine; TC, transcerebellar plane; TV, transventricular plane; TT, transthalamic plane; US, ultrasound; Vp, width of the posterior horn of lateral ventricle; YOLO, You Only Look Once algorithm. * if not otherwise specified: number of patients ** fully automated AI-driven software update has currently been released *** potential clinical value ‡ withdrawn article

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3.1. AI in GA Prediction

Reliable methods for accurate GA estimation in the second and third trimester of pregnancy remains an unsolved challenge in obstetrics. This might be addressed to late booking, infrequent access to prenatal care, and unavailability of early US examination and other reasons [63]. Namburete et al. introduced a model which was able to characterize the neuroanatomical appearance both spatially and temporally while identifying relevant brain regions such as the Sylvian fissure, cingulate and callosal sulci as powerful image regions in the GA-discrimination task [42]. The authors extended in addition to clinically relevant metadata like the head circumference canonical features sets (e.g., Haar-like features) to capture structural changes within the fetal brain. The algorithm improved the confidence of age predictions provided by the clinical HC method by ±0.64 days and ±4.57 days in the second and third trimesters, respectively. A similar approach estimates GA on standard transthalamic axial plane images using a supervised DL model (quantusGA) that automatically detects the position and orientation of the fetal brain by detecting the skull and five internal key points (necessary to crop and rotate the brain, resulting in a horizontally aligned brain image). The model then extracts textural and size information from the brain pixels and uses this information to give an estimate on the respective GA with a similar or even lower error compared with fetal biometric parameters, especially in the third trimester [63]. AI models are capable of estimation of GA with an accuracy comparable to that of trained sonographers conducting standard fetal biometry (e. g. fetal head) as the results of a recent study suggest. The authors trained an DL algorithm to estimate GA from blind US sweeps and showed that the model's performance appears to extend to blind sweeps collected by untrained providers in low-resource settings [84]. Similar results were demonstrated by two groups where ML-based algorithms outperformed current ultrasound-based clinical biometry in GA prediction with a mean absolute error of 3.0 and 4.3 days [85] or 1.51 days (using an ensemble model of both unlabeled image and video data) in second and third trimester fetuses [86].

3.2. AI for Augmenting Fetal Pose Estimation and CNS Anomaly Assessment

In the recent past, CNNs and other deep learning architectures were trained to recognize and predict fetal poses from imaging data [25,66,87,88]. In contrast to already established methods, which were mainly designed for standard plane identification assuming that a good US image quality has already been achieved with the fetus in a proper position and therefore only assist in prenatal image analysis, a study group from the UK recently emphasized the utility of recognizing the probe's proximity to diagnostic CNS planes, facilitating earlier and more precise adjustments during 2D US scanning. The semi-supervised segmentation and classification model used an 18-layer residual CNN (ResNet-18) that was trained on both labeled standard planes and unlabeled 3D US volume slices to filter out frames lacking the brain and that was able to generate masks for those containing it, enhancing the relevance of plane pose regression in a clinical setting [81]. In a previous study the authors applied a similar 18-layer residual CNN as a backbone for feature extraction (with the pre-trained ImageNet weights) and 6D pose prediction (refers to the task of determining the six degree-of-freedom pose of an object in 3D space) of arbitrarily oriented planes slicing the fetal brain US volume without the need for real ground truth data in real-time or 3D volume scans of the fetus beforehand [72].

Yeung and colleagues proposed an algorithm for a more general task of predicting the location of any arbitrary 2D US plane of the fetal brain in a pre-defined 3D space [66]. In their work they demonstrated that, based on extensive data augmentation and complementary information from training volumes acquired at different orientations, the prediction made by a novel CNN model generalizes to real 2D US acquisitions and videos, despite the model having only been trained with artificially sampled 2D slices. Considering that 3D volumes provide more effective spatial information and exhibit higher degrees of freedom (DoF), increased variations in fetal poses make proper learning for these algorithms challenging. In fact, 6D fetal pose estimation refers to the process of determining the six degrees of freedom (6DoF) position including three translational (position)

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and three rotational (orientation) parameters, allowing for a comprehensive understanding of the fetus's spatial position in a coordinate system and movement in utero. The study conducted by Chen and co-workers dealt with a similar topic - fetal pose estimation in 3D US. The authors introduced a novel 3D fetal pose estimation framework (FetusMapV2) which was able to identify a set of 22 anatomical landmarks of first and early second trimester fetuses and their specific connections to provide a comprehensive and systematic representation of the fetal pose in 3D space, to overcome challenging issues such as poor image quality, limited GPU memory for tackling high dimensional data, symmetrical or ambiguous anatomical structures, and considerable variations in fetal poses [87].

Xu and co-workers trained a DL algorithm (a cycle-consistent adversarial network (Cycle-GAN) to simulate realistic fetal neurosonography images specifically generating third-trimester pregnancy US images from second-trimester images that were qualitatively evaluated by experienced sonographers [56]. The vast majority (84.2%) of the simulated third-trimester images could not be distinguished from real third-trimester images in this study. These generative adversarial networks (GANs), first introduced by Goodfellow et al. in 2014, are algorithmic architectures that use two neural networks, competing against the other and learn to generate new, synthetic instances of data with a probalistic model that can pass for real data/images, augmenting existing datasets for training DL models [89,90]. Generative approaches can better handle missing data in multi-modal datasets by generating the missing image information and preserving sample size, thereby boosting downstream classification performance [91,92]. GANs might also assist in analyzing abnormal fetal anatomical structures (e. g. CNS anomalies) while considering also the corresponding GA information (wide range of physiological changes among trimesters leading to marked inter- and intra-organ variability) [18]. A recent research paper introduced a state-of-the-art framework (FetalBrainAwareNet) that leverages an image-to-image translation algorithm and utilizes class activation maps (CAM) as a prior in its conditional adversarial training process being capable of producing more realistic synthetic images, resulting, according to the authors, in a greater clinical relevance than similar experimental approaches [56,67,93,94]. The uniqueness of this approach was the incorporation of anatomy-aware regularization terms - one ensuring the generation of elliptical fetal skulls while the other was crucial for refining and distinctly differentiating key anatomical landmarks (e.g., cerebellum, thalami, cavum septi pellucidi, lateral ventricles) in each particular fetal head standard plane (FHSP).

In US imaging the presence of speckle noise degrades the signal-to-noise of US images, traditional image denoising algorithms often fail to fully reduce speckle noise and retain image features. A recently proposed GAN based on U-Net with residual dense connectivity (GAN-RW) achieved the most advanced despeckling performance on US images (e. g. fetal head) in terms of the peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and subjective visual effect [95]. Yeung et al. proposed a novel framework (ImplicitVol), a sensor-free approach to reconstruct 3D US volumes from a sparse set of 2D images with deep implicit representation. The authors stated that their algorithm outperformed conventional approaches in terms of image quality of the reconstructed template, as well as the refinement of the spatial 3D localization, which underscored the additional potential in slice-to-volume registration [82]. The latter refers to vital technique in medical imaging that transforms 2D slices into a cohesive 3D volume, thereby enhancing the ability to visualize and analyze complex anatomical structures, leading to optimized diagnostic (and therapeutic) outcomes. The same group introduced a multilayer perceptron network (RapidVol) to speed up slice-to-volume ultrasound reconstruction following a tri-planar decomposition of original 3D brain volumes and were able to demonstrate a threefold quicker and a 46 % more accurate complete 3D reconstruction of the fetal brain (collected as part of the INTERGROWTH-21st study) compared to the aforementioned implicit approach [96].

Lin et al. developed a real-time artificial intelligence-aided image recognition system based on the YOLO (You Only Look Once) algorithm (Prenatal Ultrasound Diagnosis Artificial Intelligence Conduct System; PAICS) being capable of detecting a set of fetal intracranial malformations. The algorithm was trained on 44,000 images and 169 videos and achieved an excellent performance on

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both internal and external validation, with accuracy comparable to that of expert sonologists [73]. The same group conducted a randomized control trial that assessed the efficacy of a deep learning system (PAICS), in assisting fetal intracranial malformation detection. More than 700 images/videos were interactively assessed by 36 operators with different levels of expertise. With the use of PAICS (prior or after individual interpretation) an increase in detection rates of fetal intracranial malformations from neurosonographic data could be noticed [77].

3.3. Other Current AI Applications Related to Fetal Neurosonography

The recent rapid emerging subfield of AI concerning the interaction between computers and human language is known as natural language processing (NLP). The launch of the chatbot ChatGPT, a large language model (LLM), in 2022, based on an NLP model known as the Generative Pretrained Transformer (GPT), has generated a wide range of thinkable applications in healthcare [97–99]. Therefore, beyond the field of (often cited) scientific writing, identifying suitable areas of application in obstetrics and gynecology, including fetal neurosonography, is obvious. It is crucial to understand that ChatGPT, trained on massive amounts of text data, mimic statistical patterns of human language, generates outputs based on probabilities and thus, emulating human conversation dynamics [97,98,100,101]. Before addressing potential applications of ChatGPT in the context of fetal neurosonography, two fundamental, its capability limitating aspects, must be kept in mind, whose knowledge must never be ignored in the interpretation of the subsequent thoughts: although ChatGPT should increasingly be capable of generating meaning-semblant behavior, the current technology lacks semantic understanding [102]. Be aware of hallucinations and fact fabrications [98]. Furthermore, the generated content suffers from an absence of verifiable references [99–101].

Most recently, the latest version of ChatGPT (GPT-4) has been evaluated for its use to facilitate referrals for fetal echocardiography to improve early detection and outcomes related to congenital heart defects (CHD) [103]. Kopylov et al. found moderate agreement between ChatGPT and experts. Comparing AI referrals to experts indicated agreement of around 80% ($p< 0.001$). For minor CHD cases, the AI referral rate was 65% compared to 47% for experts. In future, AI could presumably support clinicians in this area.

A similar approach would be conceivable for fetal neurosonography, as well as the implementation of language-based AI support in summarizing the findings and optimizing the wording of complex medical reports or even the classification of various sonographic CNS abnormalities into corresponding disease entities with differential diagnoses. In summary, ChatGPT cannot be used independently of experts in the field of fetal neurosonography and certainly will not replace them [100,104]. We agree with other authors concerning its unlikely that ChatGPT, even in improved versions, will ever be able to provide reliable data at the standard required by evidence-based medicine [100,105]. However, repetitive, time-consuming tasks and trains of thought can soon be left to this chatbot in clinical routine.:

4. Perspectives

AI-based applications, on whose algorithms prenatal diagnostics will increasingly depend on, are fundamentally changing the way clinicians use US. Even if the development of AI-based applications in obstetric US is still in its infancy and automation has not yet reached the required level of clinical application, any time soon, the use of AI in fetal neurosonography would exceed the capabilities of human experts, as in other fields of fetal US (11,14).

A recently published paper introduced a novel approach that parameterizes 3D volume data as a deep neural network, which jointly refines the 2D-to-3D registrations and learns a full 3D reconstruction based on only a set of non-sensor-tracked freehand 2D scans [82].

Unfortunately, the black-box nature of most machine learning models remains unresolved, and many decisions of intelligent systems still lack interpretable explanation. Explainable AI (XAI) is deemed to provide methods, equations and tools to make the results generated by an AI algorithm comprehensible for the user. By providing visual and feature-based explanations, XAI enhances the transparency and trustworthiness of AI predictions and could thus pave the way of initial uptake of

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an AI model into clinical routine [106]. In this regard, a recent study analyzed the performance of several CNN trained on 12,400 images on fetal (CNS) plane detection after input (image) enhancement by adopting Histogram Equalization and Fuzzy Logic based contrast enhancement. The results achieved an accuracy between 83.4 and 90 % (depending on the classifier analyzed) and were subsequently evaluated by applying LIME (Local Interpretable Model-Agnostic Explanations) and GradCAM (Gradient-weighted Class Activation Mapping) algorithms to examine the decision-making process of the classifiers, providing explainability for their outputs [107]. These XAI models visually depict the region of the image contributing to a particular class, thereby justifying why the model predicted that class [108]. Very recently, Pegios and co-workers used iterative counterfactual explanations to generate realistic high-quality CNS standard planes from low-quality non-standard ones. With their experimental approach (Diff-ICE) they demonstrated the superior value for the challenging task of fetal ultrasound quality assessment as well as its potential for future applications [109]. To alleviate the risks of incomprehensibility and - more crucial - clinical irrelevance in forthcoming research two publications proposed directive guidelines for transparent ML systems in medical image analysis (INTRPRT/Clinical XAI Guidelines) [110,111]. Interestingly, all sixteen commonly used heatmap XAI techniques evaluated by Jin et al. were found to be insufficient for clinical use due to their failure in the criteria 'truthfulness' and 'plausibility' [111].

Acknowledging the recent achievements of AI in medical image analysis, Sendra-Balcells and co-workers addressed the paradox that the development of AI in rural areas in the world, like the Sub-Saharan Africa, is at its lowest level and on the other hand the current AI advancements including deep learning implementations into prenatal US diagnosis that facilitate an improved antenatal screening. In this regard they investigated the generalizability of fetal US deep learning models to low-resource imaging settings [112]. The authors pre-trained a DL framework for standard plane detection (e. g. fetal brain) in centers with greater access to large clinical imaging datasets and subsequently applied this model to African settings. These results gained from transfer learning exemplify that domain adaptation might be a solution to support prenatal care in low-income countries.

As a recent commentary given by Tonni and Grisolia correctly stated, we will inevitably face that the incorporation of AI solutions within the US apparatus will start to surge exponentially in the near future, producing beneficial effects not only in terms of diagnostic accuracy but also producing positive effects on the quality of fetal examination in its entirety, including appropriate surveying of complex anatomical structures (e. g. fetal CNS and heart), reporting, and improving medical-legal issues for physicians involved in both fetal imaging and fetomaternal care [113].

5. Conclusions

AI has increasingly been accepted as a fundamental component in a multitude of healthcare applications such as medical image analysis. In the light of this inevitable and intriguing flooding of intelligent algorithms into modern US diagnostics nothing less than the beginning of a new era of 5D ultrasound has been proclaimed. However, there are several challenges of AI deployment particularly in fetal neurosonography that must be solved: the need for large and diverse training datasets (2D/3D) in general; the difficulty of training accurate models for diagnosing evolving fetal brain abnormalities, and the potential for algorithmic biases; the urgent need to address the troubling lack of transparency and interpretability of current AI algorithms to achieve further translation into clinical diagnostic circuits and to avoid reluctance to use if AI models seemingly only demonstrate a benefit on the optimal patient; and the seamless integration of AI models into diagnostic workflows requires careful consideration of ethical and legal implications, as well as the need for rigorous validation studies to ensure the safety and efficacy of AI applications.

However, it remains to be seen how fast and in what manner promising techniques like 6D fetal pose estimation, slice-to-volume registration tools, and real-time recognition of normal and abnormal CNS anatomy, to name a few, will be integrated into clinical practice and medical education, alongside the continued advancement of current, already commercialized AI frameworks.

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References

1. Morris JK, Wellesley DG, Barisic I, et al. Epidemiology of congenital cerebral anomalies in Europe: a multicentre, population- based EUROCAT study. Archives of Disease in Childhood. 2019;104(12):1181-1187.
2. Tagliabue G, Tessandori R, Caramaschi F, et al. Descriptive epidemiology of selected birth defects, areas of Lombardy, Italy, 1999. Popul Health Metr. 2007;5:4.
3. Paladini D, Malinger G, Birnbaum R, et al. ISUOG Practice Guidelines (updated): sonographic examination of the fetal central nervous system. Part 2: performance of targeted neurosonography. Ultrasound Obstet Gynecol. 2021;57(4):661-671.
4. Yagel S, Valsky DV. Re: ISUOG Practice Guidelines (updated): sonographic examination of the fetal central nervous system. Part 1: performance of screening examination and indications for targeted neurosonography. Ultrasound Obstet Gynecol. 2021;57(1):173-174.
5. Snoek R, Albers MEWA, Mulder EJH, et al. Accuracy of diagnosis and counseling of fetal brain anomalies prior to 24 weeks of gestational age. The Journal of Maternal-Fetal & Neonatal Medicine. 2018;31(16):2188-2194.
6. Group EW. Role of prenatal magnetic resonance imaging in fetuses with isolated mild or moderate ventriculomegaly in the era of neurosonography: international multicenter study. Ultrasound Obstet Gynecol. 2020;56(3):340-347.
7. Dall'Asta A, Paramasivam G, Basheer SN, Whitby E, Tahir Z, Lees C. How to obtain diagnostic planes of the fetal central nervous system using three-dimensional ultrasound and a context-preserving rendering technology. Am J Obstet Gynecol. 2019;220(3):215-229.
8. Di Mascio D, Buca D, Rizzo G, et al. Methodological Quality of Fetal Brain Structure Charts for Screening Examination and Targeted Neurosonography: A Systematic Review. Fetal Diagn Ther. 2022;49(4):145-158.
9. Boutet ML, Eixarch E, Ahumada-Droguett P, et al. Fetal neurosonography and infant neurobehavior following conception by assisted reproductive technology with fresh or frozen embryo transfer. Ultrasound Obstet Gynecol. 2022;60(5):646-656.
10. Bastiaansen WAP, Klein S, Koning AHJ, Niessen WJ, Steegers-Theunissen RPM, Rousian M. Computational methods for the analysis of early-pregnancy brain ultrasonography: a systematic review. EBioMedicine. 2023;89:104466.
11. Horgan R, Nehme L, Abuhamad A. Artificial intelligence in obstetric ultrasound: A scoping review. Prenat Diagn. 2023;43(9):1176-1219.
12. Jost E, Kosian P, Jimenez Cruz J, et al. Evolving the Era of 5D Ultrasound? A Systematic Literature Review on the Applications for Artificial Intelligence Ultrasound Imaging in Obstetrics and Gynecology. J Clin Med. 2023;12(21).
13. Torres HR, Morais P, Oliveira B, et al. A review of image processing methods for fetal head and brain analysis in ultrasound images. Comput Methods Programs Biomed. 2022;215:106629.
14. Xiao S, Zhang J, Zhu Y, et al. Application and Progress of Artificial Intelligence in Fetal Ultrasound. J Clin Med. 2023;12(9).
15. Dhombres F, Bonnard J, Bailly K, Maurice P, Papageorghiou AT, Jouannic JM. Contributions of Artificial Intelligence Reported in Obstetrics and Gynecology Journals: Systematic Review. J Med Internet Res. 2022;24(4):e35465.
16. Yousef R, Gupta G, Yousef N, Khari M. A holistic overview of deep learning approach in medical imaging. Multimed Syst. 2022;28(3):881-914.
17. Drukker L, Noble JA, Papageorghiou AT. Introduction to artificial intelligence in ultrasound imaging in obstetrics and gynecology. Ultrasound Obstet Gynecol. 2020;56(4):498-505.
18. Fiorentino MC, Villani FP, Di Cosmo M, Frontoni E, Moccia S. A review on deep-learning algorithms for fetal ultrasound- image analysis. Med Image Anal. 2023;83:102629.
19. Ramirez Zegarra R, Ghi T. Use of artificial intelligence and deep learning in fetal ultrasound imaging. Ultrasound Obstet Gynecol. 2023;62(2):185-194.
20. Ghabri H, Alqahtani MS, Ben Othman S, et al. Transfer learning for accurate fetal organ classification from ultrasound images: a potential tool for maternal healthcare providers. Sci Rep. 2023;13(1):17904.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 31 July 2024 doi:10.20944/preprints202407.2395.v1

21. Box GEP. Robustness in the Strategy of Scientific Model Building. In: Launer RL, Wilkinson GN, eds. Robustness in Statistics. Academic Press; 1979:201-236.
22. Yeo L, Romero R. New and advanced features of fetal intelligent navigation echocardiography (FINE) or 5D heart. J Matern Fetal Neonatal Med. 2022;35(8):1498-1516.
23. Namburete AIL, Papież BW, Fernandes M, et al. Normative spatiotemporal fetal brain maturation with satisfactory development at 2 years. Nature. 2023;623(7985):106-114.
24. Moser F, Huang R, Papież BW, Namburete AIL. BEAN: Brain Extraction and Alignment Network for 3D Fetal Neuro sonography. Neuroimage. 2022;258:119341.
25. Namburete AIL, Xie W, Yaqub M, Zisserman A, Noble JA. Fully-automated alignment of 3D fetal brain ultrasound to a canonical reference space using multi-task learning. Med Image Anal. 2018;46:1-14.
26. Moser F, Huang R, Papageorghiou AT, Papież BW, Namburete A. Automated fetal brain extraction from clinical ultrasound volumes using 3d convolutional neural networks. Cham: Springer International Publishing; 2020.
27. Gholipour A, Rollins CK, Velasco-Annis C, et al. A normative spatiotemporal MRI atlas of the fetal brain for automatic segmentation and analysis of early brain growth. Sci Rep. 2017;7(1):476.
28. Gembicki M, Welp A, Scharf JL, Dracopoulos C, Weichert J. A Clinical Approach to Semiautomated Three-Dimensional Fetal Brain Biometry-Comparing the Strengths and Weaknesses of Two Diagnostic Tools: 5DCNS+(TM) and SonoCNS(TM). J Clin Med. 2023;12(16).
29. Welp A, Gembicki M, Dracopoulos C, Scharf JL, Rody A, Weichert J. Applicability of a semiautomated volumetric ap proach (5D CNS+™) for detailed antenatal reconstruction of abnormal fetal CNS anatomy. BMC Med Imaging. 2022;22(1):154.
30. Welp A, Gembicki M, Rody A, Weichert J. Validation of a semiautomated volumetric approach for fetal neurosonogra phy using 5DCNS+ in clinical data from > 1100 consecutive pregnancies. Childs Nerv Syst. 2020;36(12):2989-2995.
31. Lu JLA, Resta S, Marra MC, Patelli C, Stefanachi V, Rizzo G. Validation of an automatic software in assessing fetal brain volume from three dimensional ultrasonographic volumes: Comparison with manual analysis. J Clin Ultrasound. 2023;51(7):1146-1151.
32. Alzubaidi M, Agus M, Alyafei K, et al. Toward deep observation: A systematic survey on artificial intelligence tech niques to monitor fetus via ultrasound images. iScience. 2022;25(8):104713.
33. Tang X. The role of artificial intelligence in medical imaging research. BJR Open. 2020;2(1):20190031.
34. Rizzo G, Aiello E, Pietrolucci ME, Arduini D. The feasibility of using 5D CNS software in obtaining standard fetal head measurements from volumes acquired by three-dimensional ultrasonography: comparison with two-dimensional ultrasound. J Matern Fetal Neonatal Med. 2016;29(14):2217-2222.
35. Rizzo G, Capponi A, Persico N, et al. 5D CNS+ Software for Automatically Imaging Axial, Sagittal, and Coronal Planes of Normal and Abnormal Second-Trimester Fetal Brains. J Ultrasound Med. 2016;35(10):2263-2272.
36. Ambroise Grandjean G, Hossu G, Bertholdt C, Noble P, Morel O, Grangé G. Artificial intelligence assistance for fetal head biometry: Assessment of automated measurement software. Diagn Interv Imaging. 2018;99(11):709-716.
37. Pluym ID, Afshar Y, Holliman K, et al. Accuracy of automated three-dimensional ultrasound imaging technique for fetal head biometry. Ultrasound Obstet Gynecol. 2021;57(5):798-803.
38. Han X, Yu J, Yang X, et al. Artificial intelligence assistance for fetal development: evaluation of an automated software for biometry measurements in the mid-trimester. BMC Pregnancy Childbirth. 2024;24(1):158.
39. Yaqub M, Napolitano R, Ioannou C, Papageorghiou AT, Noble J. Automatic detection of local fetal brain structures in ultrasound images. Proceedings - International Symposium on Biomedical Imaging. 2012:1555-1558.
40. Cuingnet R, Somphone O, Mory B, et al. Where is my baby? A fast fetal head auto-alignment in 3D-ultrasound. Paper presented at: 2013 IEEE 10th International Symposium on Biomedical Imaging; 7-11 April 2013, 2013.
41. Sofka M, Zhang J, Good S, Zhou SK, Comaniciu D. Automatic detection and measurement of structures in fetal head ultrasound volumes using sequential estimation and Integrated Detection Network (IDN). IEEE Trans Med Imaging. 2014;33(5):1054-1070.
42. Namburete AI, Stebbing RV, Kemp B, Yaqub M, Papageorghiou AT, Alison Noble J. Learning-based prediction of gestational age from ultrasound images of the fetal brain. Med Image Anal. 2015;21(1):72-86.
43. Yaqub M, Kelly B, Papageorghiou AT, Noble JA. Guided Random Forests for Identification of Key Fetal Anatomy and Image Categorization in Ultrasound Scans. Paper presented at: Medical Image Computing and Computer-Assisted Interven tion – MICCAI 2015; 2015//, 2015; Cham.
44. Baumgartner CF, Kamnitsas K, Matthew J, Smith S, Kainz B, Rueckert D. Real-Time Standard Scan Plane Detection and Localisation in Fetal Ultrasound Using Fully Convolutional Neural Networks. Paper

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 31 July 2024 doi:10.20944/preprints202407.2395.v1

presented at: Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016; 2016//, 2016; Cham.
45. Sridar P, Kumar A, Quinton A, Nanan R, Kim J, Krishnakumar R. Decision Fusion-Based Fetal Ultrasound Image Plane Classification Using Convolutional Neural Networks. Ultrasound Med Biol. 2019;45(5):1259-1273.
46. Yaqub M, Kelly B, Papageorghiou AT, Noble JA. A Deep Learning Solution for Automatic Fetal Neurosonographic Diagnostic Plane Verification Using Clinical Standard Constraints. Ultrasound Med Biol. 2017;43(12):2925-2933.
47. Qu R, Xu G, Ding C, Jia W, Sun M. Deep Learning-Based Methodology for Recognition of Fetal Brain Standard Scan Planes in 2D Ultrasound Images. IEEE Access. 2020;8:44443-44451.
48. Huang R, Xie W, Alison Noble J. VP-Nets : Efficient automatic localization of key brain structures in 3D fetal neuroso nography. Med Image Anal. 2018;47:127-139.
49. Huang R, Namburete A, Noble A. Learning to segment key clinical anatomical structures in fetal neurosonography informed by a region-based descriptor. J Med Imaging (Bellingham). 2018;5(1):014007.
50. van den Heuvel TLA, de Bruijn D, de Korte CL, Ginneken BV. Automated measurement of fetal head circumference using 2D ultrasound images. PLoS One. 2018;13(8):e0200412.
51. Dou H, Yang X, Qian J, et al. Agent with Warm Start and Active Termination for Plane Localization in 3D Ultrasound. Paper presented at: Medical Image Computing and Computer Assisted Intervention – MICCAI 2019; 2019//, 2019; Cham.
52. Sahli H, Mouelhi A, Ben Slama A, Sayadi M, Rachdi R. Supervised classification approach of biometric measures for automatic fetal defect screening in head ultrasound images. J Med Eng Technol. 2019;43(5):279-286.
53. Alansary A, Oktay O, Li Y, et al. Evaluating reinforcement learning agents for anatomical landmark detection. Med Image Anal. 2019;53:156-164.
54. Lin Z, Li S, Ni D, et al. Multi-task learning for quality assessment of fetal head ultrasound images. Med Image Anal. 2019;58:101548.
55. Bastiaansen WAP, Rousian M, Steegers-Theunissen RPM, Niessen WJ, Koning A, Klein S. Towards Segmentation and Spatial Alignment of the Human Embryonic Brain Using Deep Learning for Atlas-Based Registration. Paper presented at: Biomedical Image Registration; 2020//, 2020; Cham.
56. Xu Y, Lee LH, Drukker L, Yaqub M, Papageorghiou AT, Noble AJ. Simulating realistic fetal neurosonography images with appearance and growth change using cycle-consistent adversarial networks and an evaluation. J Med Imaging (Bellingham). 2020;7(5):057001.
57. Ramos R, Olveres J, Escalante-Ramírez B, Arámbula Cosío F. Deep learning approach for cerebellum localization in prenatal ultrasound images. Vol 11353: SPIE; 2020.
58. Maraci MA, Yaqub M, Craik R, et al. Toward point-of-care ultrasound estimation of fetal gestational age from the trans- cerebellar diameter using CNN-based ultrasound image analysis. J Med Imaging (Bellingham). 2020;7(1):014501.
59. Chen X, He M, Dan T, et al. Automatic Measurements of Fetal Lateral Ventricles in 2D Ultrasound Images Using Deep Learning. Front Neurol. 2020;11:526.
60. Xie B, Lei T, Wang N, et al. Computer-aided diagnosis for fetal brain ultrasound images using deep convolutional neural networks. Int J Comput Assist Radiol Surg. 2020;15(8):1303-1312.
61. Xie HN, Wang N, He M, et al. Using deep-learning algorithms to classify fetal brain ultrasound images as normal or abnormal. Ultrasound Obstet Gynecol. 2020;56(4):579-587.
62. Zeng Y, Tsui PH, Wu W, Zhou Z, Wu S. Fetal Ultrasound Image Segmentation for Automatic Head Circumference Biometry Using Deeply Supervised Attention-Gated V-Net. J Digit Imaging. 2021;34(1):134-148.
63. Burgos-Artizzu XP, Coronado-Gutiérrez D, Valenzuela-Alcaraz B, et al. Analysis of maturation features in fetal brain ultrasound via artificial intelligence for the estimation of gestational age. Am J Obstet Gynecol MFM. 2021;3(6):100462.
64. Gofer S, Haik O, Bardin R, Gilboa Y, Perlman S. Machine Learning Algorithms for Classification of First-Trimester Fetal Brain Ultrasound Images. J Ultrasound Med. 2022;41(7):1773-1779.
65. Skelton E, Matthew J, Li Y, et al. Towards automated extraction of 2D standard fetal head planes from 3D ultrasound acquisitions: A clinical evaluation and quality assessment comparison. Radiography (Lond). 2021;27(2):519-526.
66. Yeung PH, Aliasi M, Papageorghiou AT, Haak M, Xie W, Namburete AIL. Learning to map 2D ultrasound images into 3D space with minimal human annotation. Med Image Anal. 2021;70:101998.
67. Montero A, Bonet-Carne E, Burgos-Artizzu XP. Generative Adversarial Networks to Improve Fetal Brain Fine-Grained Plane Classification. Sensors (Basel). 2021;21(23).
68. Moccia S, Fiorentino MC, Frontoni E. Mask-R2CNN: a distance-field regression version of Mask-RCNN for fetal-head delineation in ultrasound images. International Journal of Computer Assisted Radiology and Surgery. 2021;16(10):1711-1718.

 doi:10.20944/preprints202407.2395.v1

69. Wyburd MK, Hesse LS, Aliasi M, et al. Assessment of Regional Cortical Development Through Fissure Based Gesta tional Age Estimation in 3D Fetal Ultrasound. Paper presented at: Uncertainty for Safe Utilization of Machine Learning in Medical Imaging, and Perinatal Imaging, Placental and Preterm Image Analysis; 2021//, 2021; Cham.
70. Shu X, Chang F, Zhang X, Shao C, Yang X. ECAU-Net: Efficient channel attention U-Net for fetal ultrasound cerebellum segmentation. Biomedical Signal Processing and Control. 2022;75:103528.
71. Hesse LS, Aliasi M, Moser F, et al. Subcortical segmentation of the fetal brain in 3D ultrasound using deep learning. Neuroimage. 2022;254:119117.
72. Di Vece C, Dromey B, Vasconcelos F, David AL, Peebles D, Stoyanov D. Deep learning-based plane pose regression in obstetric ultrasound. Int J Comput Assist Radiol Surg. 2022;17(5):833-839.
73. Lin M, He X, Guo H, et al. Use of real-time artificial intelligence in detection of abnormal image patterns in standard sonographic reference planes in screening for fetal intracranial malformations. Ultrasound Obstet Gynecol. 2022;59(3):304-316.
74. Sreelakshmy R, Titus A, Sasirekha N, et al. An Automated Deep Learning Model for the Cerebellum Segmentation from Fetal Brain Images. Biomed Res Int. 2022;2022:8342767.
75. Alzubaidi M, Agus M, Shah U, Makhlouf M, Alyafei K, Househ M. Ensemble Transfer Learning for Fetal Head Analysis: From Segmentation to Gestational Age and Weight Prediction. Diagnostics (Basel). 2022;12(9).
76. Coronado-Gutiérrez D, Eixarch E, Monterde E, et al. Automatic Deep Learning-Based Pipeline for Automatic Delinea tion and Measurement of Fetal Brain Structures in Routine Mid-Trimester Ultrasound Images. Fetal Diagn Ther. 2023;50(6):480- 490.
77. Lin M, Zhou Q, Lei T, et al. Deep learning system improved detection efficacy of fetal intracranial malformations in a randomized controlled trial. NPJ Digit Med. 2023;6(1):191.
78. Rauf F, Khan MA, Bashir AK, et al. Automated deep bottleneck residual 82-layered architecture with Bayesian optimi zation for the classification of brain and common maternal fetal ultrasound planes. Front Med (Lausanne). 2023;10:1330218.
79. Alzubaidi M, Agus M, Makhlouf M, Anver F, Alyafei K, Househ M. Large-scale annotation dataset for fetal head biometry in ultrasound images. Data Brief. 2023;51:109708.
80. Alzubaidi M, Shah U, Agus M, Househ M. FetSAM: Advanced Segmentation Techniques for Fetal Head Biometrics in Ultrasound Imagery. IEEE Open J Eng Med Biol. 2024;5:281-295.
81. Di Vece C, Cirigliano A, Le Lous M, et al. Measuring proximity to standard planes during fetal brain ultrasound scanning. ArXiv. 2024;abs/2404.07124.
82. Yeung PH, Hesse LS, Aliasi M, Haak MC, Xie W, Namburete AIL. Sensorless volumetric reconstruction of fetal brain freehand ultrasound scans with deep implicit representation. Med Image Anal. 2024;94:103147.
83. Dubey G, Srivastava S, Jayswal AK, Saraswat M, Singh P, Memoria M. Fetal Ultrasound Segmentation and Measurements Using Appearance and Shape Prior Based Density Regression with Deep CNN and Robust Ellipse Fitting. J Imaging Inform Med. 2024;37(1):247-267.
84. Pokaprakarn T, Prieto JC, Price JT, et al. AI Estimation of Gestational Age from Blind Ultrasound Sweeps in Low-Resource Settings. NEJM Evid. 2022;1(5).
85. Lee LH, Bradburn E, Craik R, et al. Machine learning for accurate estimation of fetal gestational age based on ultrasound images. NPJ Digit Med. 2023;6(1):36.
86. Lee C, Willis A, Chen C, et al. Development of a Machine Learning Model for Sonographic Assessment of Gestational Age. JAMA Netw Open. 2023;6(1):e2248685.
87. Chen C, Yang X, Huang Y, et al. FetusMapV2: Enhanced Fetal Pose Estimation in 3D Ultrasound. Medical Image Analysis. 2023.
88. Yeung P-H, Aliasi M, Haak M, Xie W, Namburete AIL. Adaptive 3D Localization of 2D Freehand Ultrasound Brain Images. Paper presented at: Medical Image Computing and Computer Assisted Intervention – MICCAI 2022; 2022//, 2022; Cham.
89. Goodfellow IJ, Pouget-Abadie J, Mirza M, et al. Generative Adversarial Nets. Paper presented at: Neural Information Processing Systems2014.
90. Wang R, Bashyam V, Yang Z, et al. Applications of generative adversarial networks in neuroimaging and clinical neu roscience. Neuroimage. 2023;269:119898.
91. Lasala A, Fiorentino MC, Micera S, Bandini A, Moccia S. Exploiting class activation mappings as prior to generate fetal brain ultrasound images with GANs. Annu Int Conf IEEE Eng Med Biol Soc. 2023;2023:1-4.
92. Wolterink JM, Mukhopadhyay A, Leiner T, Vogl TJ, Bucher AM, Išgum I. Generative Adversarial Networks: A Primer for Radiologists. Radiographics. 2021;41(3):840-857.
93. Lasala A, Fiorentino MC, Bandini A, Moccia S. FetalBrainAwareNet: Bridging GANs with anatomical insight for fetal ultrasound brain plane synthesis. Comput Med Imaging Graph. 2024;116:102405.

94. Iskandar M, Mannering H, Sun Z, et al. Towards Realistic Ultrasound Fetal Brain Imaging Synthesis. ArXiv. 2023;abs/2304.03941.
95. Zhang L, Zhang J. Ultrasound image denoising using generative adversarial networks with residual dense connectivity and weighted joint loss. PeerJ Comput Sci. 2022;8:e873.
96. Eid MC, Yeung P-H, Wyburd MK, Henriques JF, Namburete AIL. RapidVol: Rapid Reconstruction of 3D Ultrasound Volumes from Sensorless 2D Scans. ArXiv. 2024;abs/2404.10766.
97. Altmäe S, Sola-Leyva A, Salumets A. Artificial intelligence in scientific writing: a friend or a foe? Reprod Biomed Online. 2023;47(1):3-9.
98. Bhayana R. Chatbots and Large Language Models in Radiology: A Practical Primer for Clinical and Research Applications. Radiology. 2024;310(1):e232756.
99. Grünebaum A, Chervenak J, Pollet SL, Katz A, Chervenak FA. The exciting potential for ChatGPT in obstetrics and gynecology. Am J Obstet Gynecol. 2023;228(6):696-705.
100. Lee Y, Kim SY. Potential applications of ChatGPT in obstetrics and gynecology in Korea: a review article. Obstet Gynecol Sci. 2024;67(2):153-159.
101. Youssef A. Unleashing the AI revolution: exploring the capabilities and challenges of large language models and text-to-image AI programs. Ultrasound Obstet Gynecol. 2023;62(2):308-312.
102. Titus LM. Does ChatGPT have semantic understanding? A problem with the statistics-of-occurrence strategy. Cognitive Systems Research. 2024;83:101174.
103. Kopylov LG, Goldrat I, Maymon R, Svirsky R, Wiener Y, Klang E. Utilizing ChatGPT to facilitate referrals for fetal echocardiography. Fetal Diagnosis and Therapy. 2024:1-1.
104. Braun E-M, Juhasz-Böss I, Solomayer E-F, et al. Will I soon be out of my job? Quality and guideline conformity of ChatGPT therapy suggestions to patient inquiries with gynecologic symptoms in a palliative setting. Archives of Gynecology and Obstetrics. 2024;309(4):1543-1549.
105. Haverkamp W, Tennenbaum J, Strodthoff N. ChatGPT fails the test of evidence-based medicine. Eur Heart J Digit Health. 2023;4(5):366-367.
106. Fischer A, Rietveld A, Teunissen P, Hoogendoorn M, Bakker P. What is the future of artificial intelligence in obstetrics? A qualitative study among healthcare professionals. BMJ Open. 2023;13(10):e076017.
107. Rahman R, Alam MGR, Reza MT, et al. Demystifying evidential Dempster Shafer-based CNN architecture for fetal plane detection from 2D ultrasound images leveraging fuzzy-contrast enhancement and explainable AI. Ultrasonics. 2023;132:107017.
108. Harikumar A, Surendran S, Gargi S. Explainable AI in Deep Learning Based Classification of Fetal Ultrasound Image Planes. Procedia Computer Science. 2024;233:1023-1033.
109. Pegios P, Lin M, Weng N, et al. Diffusion-based Iterative Counterfactual Explanations for Fetal Ultrasound Image Quality Assessment. ArXiv. 2024;abs/2403.08700.
110. Chen H, Gomez C, Huang CM, Unberath M. Explainable medical imaging AI needs human-centered design: guidelines and evidence from a systematic review. NPJ Digit Med. 2022;5(1):156.
111. Jin W, Li X, Fatehi M, Hamarneh G. Guidelines and evaluation of clinical explainable AI in medical image analysis. Med Image Anal. 2023;84:102684.
112. Sendra-Balcells C, Campello VM, Torrents-Barrena J, et al. Generalisability of fetal ultrasound deep learning models to low-resource imaging settings in five African countries. Sci Rep. 2023;13(1):2728.
113. Tonni G, Grisolia G. Simulator, machine learning, and artificial intelligence: Time has come to assist prenatal ultrasound diagnosis. J Clin Ultrasound. 2023;51(7):1164-1165.