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Review Article

Advancements in artificial intelligence for pelvic floor ultrasound analysis

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Abstract: Pelvic floor ultrasound provides a clear depiction of pelvic floor structures and their spatial anatomical relationships, enabling enhanced observation of pelvic organ function and position. The integration of artificial intelligence (AI) into medical imaging has revolutionized the automatic analysis of imaging data, offering efficient and accurate preprocessing and analysis. This technological advance addresses challenges associated with traditional pelvic floor ultrasound, such as reliance on operator's experience, time-intensive manual measurements, and significant potential for human error. Current AI applications in pelvic floor ultrasound encompass automatic measurement of the angle of progress (AOP), automatic segmentation of the levator hiatus (LH), and automatic identification of the levator ani muscle (LAM). AI excels in mimicking human analysis, distilling patterns from reorganized data. This paper, grounded in a comprehensive literature review, outlines the principal aspects of pelvic floor ultrasound and its augmentation through AI, highlighting the application value and progress of AI in this field.

Keywords: Pelvic floor ultrasound, Artificial intelligence, Angle of progress, Levator hiatus, Levator ani

Introduction

Pelvic floor ultrasound effectively captures coronal, sagittal, and cross-sectional images of target organs, facilitating comparative analysis of pelvic organ functions and positions. It plays a crucial role in diagnosing and treating female pelvic floor dysfunction, predicting prenatal and intrapartum delivery methods, and evaluating the labor process. Its advantages include the absence of radiation, high resolution, and the capability to dynamically capture complete pelvic organ ultrasound images, garnering significant attention in clinical research [1-3]. However, traditional pelvic floor ultrasound and intrapartum ultrasound monitorings face challenges due to time-consuming manual measurements and substantial human error, hindering their broader clinical application [4].

Transperineal pelvic floor ultrasound, the most prevalent method, assesses changes in the bladder, urethra, and their surrounding support structures during rest and maximum Valsalva maneuvers using 2D, 3D, and 4D imaging [5-7]. This technique involves reconstructing and imaging the collected volume data in the coronal, sagittal, and transverse planes. It measures the displacement of pelvic organs in various patient states, evaluates the integrity of the levator ani muscle (LAM) and anal sphincter, and calculates the levator hiatus (LH) area during maximum Valsalva [8-10]. LAM, a key pelvic floor muscle component comprising the iliococcygeus and pubococcygeus muscles, is vital for pelvic floor tissue support. Abnormal morphological and functional changes in LAM are often the pathological foundation for pelvic floor dysfunction [11]. LAM ultrasound imaging, which reconstructs images in contraction and Valsalva states, offers dynamic insights into morphology changes, thus providing a reliable basis for assessing postpartum pelvic floor structure and function [12]. The LH area is indicative of

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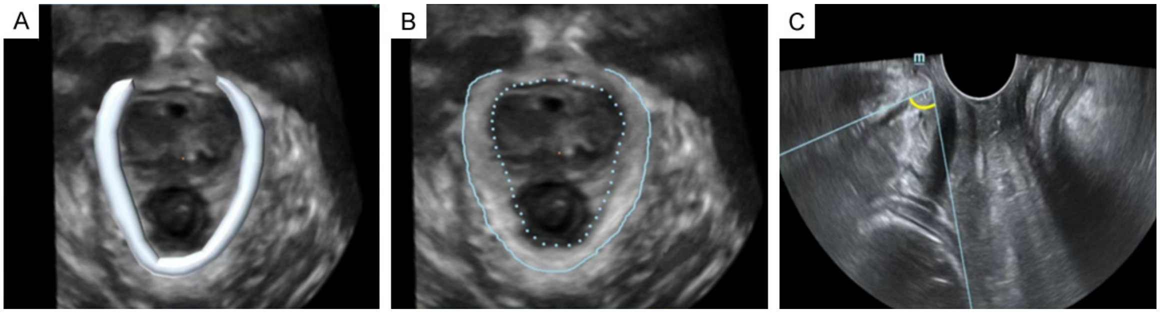

Figure 1. AI's capabilities in pelvic floor ultrasound analysis. A. Levator ani muscle volume identification diagram, showcasing volume measurements; B. Diagram identifying the levator hiatus and its length, with a dotted line marking the levator ani hiatus perimeter and a solid line indicating the levator ani length; C. Schematic for measuring the angle of progression, illustrating the technique for angle calculation.

pelvic floor muscle elasticity and compliance, with volume rendering allowing for clear visualization under maximum Valsalva [13]. Pelvic floor ultrasound also enables continuous observation of structures such as the reproductive hiatus, bladder neck, and urethra, overcoming the limitations of surface anatomy in evaluating pelvic floor function [14, 15].

Artificial intelligence (AI) technology has the capability to construct deep network models for extracting intricate features within images, as well as learning feature extraction and automatic image segmentation. This enables end-to-end training and detection, striking an optimal balance between speed and precision, and achieving diagnostic efficiency comparable to experienced physicians [16]. Given the complex morphological structure of the pelvic floor, AI excels in mimicking human analytical processes and deducing patterns from restructured data. Various deep learning algorithms have been developed to automate the recognition of pelvic floor ultrasound images, aiding physicians in swiftly assessing the function of pelvic floor organs with relatively lower labor costs [17-19]. Currently, AI's application in pelvic floor ultrasound encompasses three primary areas: automatic measurement of the angle of progress (AOP), automatic segmentation of the LH, and automatic identification of the LAM. An illustrative diagram showcasing AI's capabilities in analyzing AOP, LH, and LAM in ultrasound imagery is presented in **Figure 1**.

As AI increasingly impacts the automatic analysis of medical imaging data, numerous leading institutions globally have systematically integrated AI into image recognition. They have developed sophisticated algorithms, such as convolutional neural networks (CNN) based on deep learning, for applications including the differentiation of benign and malignant skin lesions and the diagnosis and analysis of pelvic floor disorders' biological characteristics [20-22]. Consequently, intelligent medical image interpretation, especially in pelvic floor ultrasound, is emerging as a future research focal point. Understanding the present application of AI in pelvic floor ultrasound aids in accurately determining the position of structures within the pelvic cavity and automatically identifying relevant parameter outcomes. This review focuses on assessing the application value and progress of AI in pelvic floor ultrasound.

AI's application in automatic measurement of AOP

The propulsion of the fetal head in the birth canal, influenced by the spontaneous pushing force of pregnant women and uterine contraction, is a critical variable for predicting delivery outcomes [23]. The limited accuracy of digital examination in determining the fetal head's craniofacial level and descent has led the International Society for Obstetric and Gynecologic Ultrasound to recommend AOP measurement for evaluating the fetal head position. Transperineal pelvic floor ultrasound, suggested as an auxiliary tool during the second trimester, provides more accurate and repeatable parameters than traditional palpation for determining the fetal head position [24, 25].

Angeli et al. utilized morphological filters and pattern recognition to measure AOP changes

Table 1. Literature pertaining to the application of AI in AOP automatic measurement

Author	Year	Cases	Types of models	Indicator outcome
Angeli et al. [26]	2020	27	Fully automatic	ICC(AOP)=0.99
Conversano et al. [27]	2017	39	Fully automatic	*r*(AOP)=0.99
Lu et al. [28]	2022	1964	Fully automatic	*R*(AOP)=0.964
Bai et al. [29]	2022	313	Fully automatic	ICC(AOP)=0.91
Youssef et al. [30]	2017	156	Fully automatic	ICC(AOP)=0.865

Note: AOP: angle of progress; ICC: intraclass correlation coefficient; AI: artificial intelligence.

during the active second stage of labor, accurately predicting fetal head position and delivery mode, matching the precision of experienced clinicians [intraclass correlation coefficient (ICC) =0.99] [26]. Conversano et al. overcame imaging challenges with the pubic symphysis by using its central echo as a reference point for AOP measurement, ensuring high reliability and repeatability [27]. Their method demonstrated a strong correlation (r=0.99, P<0.001) between algorithmically measured AOP values and reference standards.

Lu et al. analyzed a dataset of 1964 images, calculating AOP from segmented images of the fetal head and pubic symphysis, indicating that automated AOP measurement is efficient and could enhance pelvic floor ultrasound development [28]. Bai et al. introduced a framework incorporating image segmentation, target fitting, and AOP calculation, achieving high accuracy in automatic AOP measurement [29].

Conversely, Youssef et al. reported that in an initial evaluation of 156 pregnant women, AI accurately identified the pubic symphysis and fetal head positions in 85.3% of cases, with perfect accuracy upon reevaluation. However, they noted that AOP measurements by AI were broader than manual assessments, suggesting a need for further accuracy enhancements for clinical application [30]. The AI technique demonstrates commendable repeatability, closely aligning with manual measurements (ICC=0.865, 95% CI=0.766-0.923). However, AI-derived AOP measurements tend to be broader than those obtained manually [(119±20)° vs (130±20)°], indicating a need for further refinement in AI's accuracy for clinical integration. AI's capability to autonomously monitor changes in fetal head position and dynamically assess the AOP offers crucial insights for clinicians managing obstructed or prolonged second stages of labor.

Currently, AI models for AOP measurement diverge primarily in their approach to identifying the pubic symphysis' posterior margin: one model identifies the high-echo edge near the pubic symphysis' tail as the posterior margin, while the other locates the center point of the high-echo region without specifying the posterior margin. The former model boasts superior repeatability but risks overestimating AOP in cases of fetal scalp edema by mistaking the scalp for the skull. The latter model mitigates identification challenges, yet the reliability of this automated approach demands further validation through expansive multi-center research, addressing current limitations of small sample sizes and narrow training set selections.

Table 1 lists significant literature on AI's application in automatic AOP measurement, outlining its current use and areas requiring enhancement for effective clinical application.

Application of AI in automatic segmentation of LH

The LH, being the largest potential hernia entrance in the human body, plays a crucial role in physiological functions. Its size and shape correlate with the severity of pelvic organ prolapse, levator muscle avulsion, and the risk of organ prolapse recurrence post-surgery. Hence, precise measurement of the LH area is essential [31, 32]. Currently, the accurate delineation of LH's complete boundary largely relies on experienced clinicians, but AI technology in automatic segmentation and pattern recognition could significantly enhance the acceptability and reliability of LH measurements. Sindhwani et al., as early as 2016, introduced a semi-automatic model for LH segmentation to minimize observer variability and expedite image analysis [33]. This model involved testing with 91 representative C-plane images,

Table 2. Literature pertaining to the application of AI in LH automatic segmentation

Author	Year	Cases	Types of models	Indicator outcome
Sindhwani et al. [33]	2016	91	Semi-automatic	ICC(LH)=0.93
Chen et al. [34]	2023	100	Fully automatic	ICC(LH)=0.987
Bonmati et al. [35]	2018	91	Fully automatic	DSC(LH)=0.90
Li et al. [36]	2019	130	Fully automatic	DSC(LH)=0.96
Williams et al. [37]	2021	73	Fully automatic	DSC(LH)=0.911

Note: LH: levator hiatus; ICC: intraclass correlation coefficient; DSC: Deiss similarity coefficient; AI: artificial intelligence.

manually marking the pubic symphysis and LAM, and then integrating these marked images into a predefined template to generate the initial contour for LH's automatic segmentation. The results highlighted a substantial reduction in observer variability with the algorithm (ICC=0.93), and its speed (7.07 s) was nearly three times faster than manual contouring (21.31 s), achieving LH segmentation with just three points. Chen et al. conducted a retrospective analysis of LH raw ultrasound image data from 100 patients, using transperineal pelvic floor ultrasound for quantification. The consistency of LH area measurements between an automated intelligent pelvic system software program and manual measurement was assessed [34]. The study found a 94% satisfaction rate for automatic reconstruction, despite unsatisfactory results in 6 images due to rectal gas. The ICC for the 94 successfully reconstructed images was 0.987, indicating the automated program's effectiveness in LH reconstruction, delineation, and measurement during maximum Valsalva motion, albeit with occasional misidentification of LH's posterior boundary due to rectal gas influence. Bonmati et al. developed a fully automatic method employing a CNN to delineate LH discontinuity in two-dimensional images derived from 3-D ultrasound volumes [35]. The dataset comprised images from 91 patients marked during Valsalva, contraction, and rest phases for cross-validation training and evaluation, proposing a promising approach for automated LH segmentation.

The experimental outcomes by Bonmati et al. indicated that the fully automatic method matches the accuracy of the semi-automatic approach by Sindhwani et al. [33, 35] in LH segmentation for pelvic floor analysis. Both Williams et al. and Sindhwani et al. introduced AI-based methods for the automatic measurement of LH area, leveraging AI detection and LH contour tracking from representative C-plane images [33, 36]. These approaches demonstrate AI's capability for accurate, rapid, and reliable LH detection, significantly reducing the assessment time for pelvic floor diseases.

Li et al., after comparing their study with various published segmentation models, affirmed that a fully automatic CNN method utilizing dense connections yields more precise segmentation outcomes for LH in ultrasound images [37]. Despite these advancements, current LH segmentation models, whether semi-automatic or fully automatic, require operation within a specific MatLab environment, and all necessitate manual reconstruction of LH in 3D/4D volume data by clinicians. This process involves manually selecting the volume of interest, typically the maximum contraction volume. Moreover, challenges such as gas interference and other factors compromising ultrasound image quality can adversely affect the effectiveness of LH automatic segmentation.

Future efforts must aim to enhance the automation methods to mitigate manual intervention and address image quality issues impacting segmentation accuracy. A summary of research articles on AI's application to LH automatic segmentation is presented in **Table 2**, highlighting the need for further advancements in this area.

Application of AI in LAM automatic recognition

LAM plays a pivotal role in supporting female pelvic organs, with over one fifth of women experiencing LAM damage during vaginal delivery, potentially leading to pelvic organ prolapse and urinary incontinence [38]. Identifying LAM accurately is thus clinically crucial. Previous research developed an active model for the automatic segmentation of LAM, using manual segmentation data from 50 women for training [39]. The findings highlighted that the ICC for average echo and volume between manual and automatic segmentation were excellent and good, respectively (ICC=0.968 and 0.626), demonstrating the reliability of automatic segmentation in measuring potential clinical parameters, notably average echo.

In a 2019 study, van den Noort et al. utilized a CNN to automatically segment the plane of the smallest hiatus size, further applying this segmentation to measure LAM length and assess its reliability [40]. The largest discrepancies between automatic and manual measurements were observed at the pubic symphysis junction, which is the most challenging segment of LAM. Nonetheless, both methods showed good consistency in LAM length measurements (ICC=0.87 and 0.73). Of the 14 images that CNN failed to identify clearly, most were automatically excluded by the system due to poor image contrast or low LAM length.

Comparative analysis of different LAM automatic recognition models revealed a research gap: images of patients with LAM injury were not included, limiting the ability to compare model segmentation effectiveness for such cases. This gap underscores a limitation in AI's application to LAM automatic identification, necessitating further research to enhance repeatability, stability, and broader application in scientific research and clinical practice.

In conclusion, the integration of AI in medical imaging, particularly in pelvic floor ultrasound image recognition, offers solutions to challenges related to operator experience dependency, potentially revolutionizing the ultrasound diagnostic labor division and enhancing work efficiency. However, current research is predominantly focused on LH and LAM automatic segmentation. Challenges remain in measuring and positioning pelvic organ activity under varying conditions due to significant fluctuations, posing a significant challenge for developing more sophisticated AI algorithms. With ongoing AI advancements and the advent of the big data era, genuine AI automation in medical imaging is a promising near-future prospect.

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Disclosure of conflict of interest

None.

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