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Applications of artificial intelligence in obstetrics

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Artificial intelligence, which has been applied as an innovative technology in multiple fields of healthcare, analyzes large amounts of data to assist in disease prediction, prevention, and diagnosis, as well as in patient monitoring. In obstetrics, artificial intelligence has been actively applied and integrated into our daily medical practice. This review provides an overview of artificial intelligence systems currently used for obstetric diagnostic purposes, such as fetal cardiotocography, ultrasonography, and magnetic resonance imaging, and demonstrates how these methods have been developed and clinically applied.

Keywords: Artificial intelligence; Obstetrics; Fetal cardiotocography; Ultrasonography; Magnetic resonance imaging

Key points: Artificial intelligence (AI) is a new technology analyzing large amounts of data to assist in disease prediction, prevention, and diagnosis, as well as in patient monitoring. AI is applied to fetal cardiotocography, ultrasonography, and magnetic resonance imaging in obstetrics. AI helps to overcome various problems related to diagnosis in obstetrics.

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Introduction

Medical artificial intelligence (AI), which began to gain attention with the advent of IBM Watson Health, is rapidly developing in various fields, and efforts to refine and apply AI to clinical practice are more active than ever. In particular, technologies using AI are being commercialized in a number of fields due to the accumulation of big data, and in particular, deep learning using artificial neural networks (ANNs) for analyzing medical images has been recognized as the technology closest to clinical application. Machine learning is a basic method of AI that uses data, learns from the data, and makes decisions or predictions by itself; however, machine learning needs some guidance. Deep learning is a subtype of machine learning, through which ANNs themselves can judge the accuracy of predictions [1]. AI applications using deep learning have extended beyond computed tomography, magnetic resonance imaging (MRI), ultrasonography (US), and pathology slides to include diagnoses or determinations of disease severity using endoscopy, including optic and intestinal images [2–5]. Diverse companies have been developing and commercializing AI-based video platforms. The aim of this review was to introduce the AI technologies that are being researched and developed in the field of obstetrics.

Artificial Intelligence

AI was first introduced in the 1960s with the goal of using complex machines (i.e., computers) to simulate human intelligence. AI technology has been advanced through machine learning and deep learning [6]. Machine learning is a type of algorithm applied to process data. As a subtype of AI, machine learning focuses on the ability of machines to receive data and learn for themselves without being programmed with rules. Machine learning models can learn on their own, and then adjust and improve as they learn more about the information being processed. Machine learning algorithms are classified into supervised and unsupervised learning algorithms. Supervised learning can be further classified into classification (decision trees, support vector machines, etc.) and regression (typical regression algorithms). Unsupervised learning algorithms receive random samples, and discovering main patterns or similarities in these samples is the main goal. These approaches can be further classified into clustering (K-means or Gaussian mixture models) and dimensionality reduction. The former type of approach is commonly used when the final goal is set at the time of learning, and the latter is used as an exploratory method for which the final goal comes after the analysis [7].

Deep learning, an advanced form of machine learning, involves models constructed to analyze large amounts of data using ANNs, which are structured into multiple neural nodes, resembling the arrangement of neurons in the brain [1]. An ANN consists of a dependable mathematical system that can interpret multifactorial data. These neurons connect through multiple synapses to exchange data with each other, and in doing so, derive the most probable answer. By creating these multiple connections, computers can identify the most probable answers to problems by mimicking cognitive functions such as inference processes. This complex algorithmic AI software is now being used in medicine to analyze large amounts of data, which can help prevent, diagnose and monitor patients' diseases. For video and image processing, convolutional neural networks have been applied in deep learning; these contain deeper networks with more convolutional layers and have the ability to integrate information more deeply for image processing [8].

Medicine

In medicine, AI has gained popularity in the field of diagnostic radiology, and its domain of usage has been expanding to include many different types of imaging-based diagnoses. We would like to change as follows. AI predictive and classification models have been developed that include not only simple radiological findings (e.g., for the prostate) from breast and heart imaging, bone age, chest radiology, and laboratory results, but also combinations of above findings and pathologic images, previous medical images and omics.

Many AI methods have been used to improve the diagnostic process and to diagnose certain diseases, which humans have been doing for a long time. These methods reduce the duration of image acquisition, enable optimization of personnel requirements, and lead to diagnostic and economic benefits that result in cost-saving. One study compared 100 manual biometric measurements to 100 automated measurements and showed time-savings of about 20 seconds and seven steps in each 20-minute anatomic survey [9]. These methods are also very valuable for doctors regarding the diagnosis of patients and reduce medico-legal issues, directly and indirectly. Unfortunately, in the field of obstetrics and gynecology, the application of AI has been slower, although some AI technologies have been utilized in obstetrics. Improvements in AI are closely related to the amount of available data, which currently is linked to the frequency of imaging performed in women visiting the hospital

Fetal Cardiotocography

Cardiotocography (CTG) was an early development in the field of obstetrics. CTG is the most important device for evaluating fetal well-being through measurements of the fetal heart rate and uterine contractions. The fetal heart rate pattern reflects fetal cardiac and central nervous system responses to hemodynamic changes. Abundant research on CTG has been conducted since 1980. A recent meta-analysis indicated that a 50% reduction in neonatal seizures was associated with continuous CTG monitoring [10]. Despite its clinical importance, it is difficult to ensure objectivity between interpretations, and above all, regular observations are necessary in order to avoid a long gap between detection of suspicious patterns and intervention. To overcome limitations in the interpretation of CTG by humans, AI using modern computer systems has been applied to CTG interpretation, and many experiments are underway. AI systems are not influenced by human limitations such as fatigue, distraction, bias, poor communication, cognitive overload, or fear of doing harm.

Since the first study of CTG interpretation using machines in 1989 by Bassil et al., there have been many studies on AI and CTG interpretation, including randomized controlled trials and retrospective cohort studies. Three randomized controlled trials including over 50,000 patients yielded inconsistent outcomes regarding risk identification and the reduction of adverse outcomes. Nevertheless, retrospective studies using traditional machine learning methods showed improved sensitivity in the detection of compromised fetuses (Table 1). In addition to these studies, 21 diagnostic features were extracted based on data from 2,126 CTG

Table 1. Summary table of machine learning interpretations of CTG to determine neonatal outcomes

Study	No. of patients	AI technology	Inclusion criteria	Outcomes
Randomized controlled trials: baseline, variability, and deceleration-based				
Ignatov and Lutomski (2016) [11]	720	Quantitative CTG decision-support system; Nexus-obstetrics	Singleton, >18 years of age	Reduced risk in the interventional arm compared to control
Nunes et al. (2017) [12]	7,730	Omniview-SisPorto	Singleton, >16 years of age, >36 weeks of gestation	While a very low rate of acidosis was observed, there was no statistically significant reduction in the rate of acidosis and obstetric intervention
Brocklehurst et al. (2017) (The INFANT Trial) [13]	46,042	Infant-K2	Singleton or twin, >16 years of age, >35 weeks of gestation	Effective in identification of abnormal CTG, clinical outcomes not improved
Feature engineering theory: traditional machine learning, retrospective				
Warrick et al. (2009) [14]	220 cases	Support vector machine	Death, HIE, base deficit >12 mmol	Detected 50% of pathological cases with FPR 7.5%
Zhao et al. (2018) [15]	552 intrapartum CTG recordings	8-layer deep 2D CNN		Classify normal and pathological CTGs
Feature engineering theory: deep learning, retrospective				
Ogasawara et al. (2021) [16]	324 CTG recordings	CNN models	Umbilical artery pH <7.20 or Apgar score at 1 min <7	AUC 0.73±0.04, early detection of compromised fetuses
Georgieva et al. (2014) [17]	22,790 Cases		Acidemia (pH <7.05) and severe compromise (stillbirth, neonatal death, HIE, NICU admission)	Improved sensitivity and FPR in detecting acidemia/compromise compared with clinical practice
Liu et al. (2021) [18]	3,239 CTG recordings	Fully convolutional networks	292 singletons, ≥36 weeks of gestation	Higher sensitivity for predicting fetal compromise but a higher FPR compared with clinical practice

CTG, cardiotocography; AI, artificial intelligence; HIE, hypoxic ischemic encephalopathy; FPR, false-positive rate; CNN, convolutional neural network; NICU, neonatal intensive care unit; AUC, area under the curve.

examinations, and a deep learning-based automatic classification algorithm of CTG showed a sensitivity 99.716%, a specificity 97.500%, and an accuracy 99.503% in 2019 [19]. Another study reported an algorithm that could predict the risk of a pH of 7.15 or less in umbilical cord blood with an accuracy of 98.34%, a sensitivity of 98.22%, and a specificity of 94.87% using CTG data from 552 cases of labor [20]. However, a recent systematic review concluded that machine learning interpretation of CTG during labor did not improve neonatal outcomes in terms of neonatal acidosis, cord blood pH <7.15–7.20, 5-minute Apgar score <7, mode of delivery, neonatal intensive care unit admission, neonatal seizures, or perinatal death, and had limited reliability compared to experts [21]. A plausible reason for the limited efficacy is that the training for ML models of CTG was based on human interpretation. Therefore, an alternative approach that does not include human interpretation or guidelines in system development has been investigated in the context of feature engineering theory (Table 1). Based on these technologies, it is expected that a future program that automatically analyzes CTG and informs clinicians of risks with more advanced computer systems will be commercialized and will be useful in clinical practice.

Ultrasonography

Above all, AI is being applied and actively studied in obstetrics for the analysis of US, which generates standardized data. US is a safe, non-invasive checkup method for prenatal diagnosis. Despite the standard application of US, measurements are challenging in circumstances such as maternal obesity, motion blurring, missing boundaries, acoustic shadow, speckle noise and a low signal-to-noise ratio [22]. In addition, manual US screening is slow and susceptible to mistakes, and two-dimensional images are mostly stored in databases. Therefore, the use of new technologies to improve the primary acquired images or help extract and standardize measurements is of great importance.

Machine learning was first applied to US images of fetuses several years ago. In particular, it has become possible to acquire and distinguish different body parts of fetuses through machine learning; therefore, many studies have presented algorithms that automatically extracted and measured fetal structures and fetal biometry from US images [23]. There currently exists a semi-automatic program for fetal ultrasound analysis (it is a semi-automatic program because the program automatically performs body measurements using an AI algorithm after the sonographer or doctor selects an appropriate image of each body part). This program is already in service, and several companies are preparing to launch related services. One example involves the automatic acquisition of a standard scan plane demonstrated by assessing two-dimensional transventricular US images of the fetal brain and three-dimensional transthalamic plane US measuring the fetal biparietal diameter and head circumference [24,25]. Other studies reported efficacy using machine learning in the identification of fetal structures and organs to find congenital abnormalities [26–31]. Table 2 summarizes research on deep learning applications for fetal biometry and gross fetal imaging, including the heart and short cervix.

To obtain high-quality images within an appropriate amount of time, personnel should be trained in the skilled procedures involved in the obstetric image scanning process. Freehand ultrasound plane acquisition has been developed, but not yet standardized; however, a recent study demonstrated that a probe guidance system provided a useful navigation signal towards targets such as the standard plane of certain structures [32]. In addition, Noble et al. have been working on deep learning and interactions involved in scanning for more than a decade and developed a multi-cue data capture system for the acquisition of data based on sonographers' perceptions and actions through the application of a deep learning model [33–35]. This is accomplished by analyzing the pupillary response, voices, and actions of sonographers; furthermore, this sensation and motion tracking system would be accompanied by information about safety issues, such as the thermal index.

Fetal Echocardiography

Fetal echocardiography (ECG) has only been used for 15 years; nonetheless, this imaging modality is essential for perinatal care in that it is very useful for diagnosing and monitoring intrauterine growth restriction, twin-to-twin transfusion syndrome, and congenital heart anomalies. Monitoring fetal cardiac function with US is challenging due to involuntary movements of the fetus, the small fetal heart, the fast fetal heart rate, limited access to the fetus, and the lack of experts in fetal echocardiography. Automatic

Table 2. Deep learning research on obstetric ultrasonography

Study	Field	Total number of patients/ images	AI technology	Outcomes
Fetal biometry and gross imaging				
Burgos-Artizzu et al. (2020) [31]	Fetal anatomic planes (abdomen, brain, femur and thorax), cervix	1,792 Patients; 12,400 images	CNN	Similar performance compared to humans but limited fine-grained plane categorization
Papageorghiou et al. (2016) [36]	Gestational age estimation	4,229 Patients	Generic algorithm	Head circumference and femur length at second trimester: accurate estimation of GA
Sciortino et al. (2017) [37]	Nuchal translucency	12 Patients; 382 frames	Wavelet and multi-resolution analysis	True positive rate 99.5%, 64% of measurements with an error equal to 1 pixel
Heart				
Sulas et al. (2021) [38]	FHR	25 Patients; 43 images, 174,319 PWD segments	7 Envelope tracing techniques and 23 processing steps	98% Accuracy
Arnaout et al. (2021) [39]	Fetal heart imaging at 18–24 weeks of gestations	107,823 images	Deep learning: segmentation model	AUC of 0.99, 95% sensitivity, 96% specificity
Short cervix				
Bahado-Singh et al. (2019) [40]	Cervical length (<15 mm) combined omics, demographic and clinical data	26 Patients	Deep learning performed best among six different machine learning techniques	AUC of 0.890 delivery <34 weeks GA; 0.890 delivery <28 weeks GA after amniocentesis; 0.792 NICU admission

AI, artificial intelligence; CNN, convolutional neural network; GA, gestational age; FHR, fetal heart rate; PWD, pulsed-wave Doppler; AUC, area under the curve; NICU, neonatal intensive care unit.

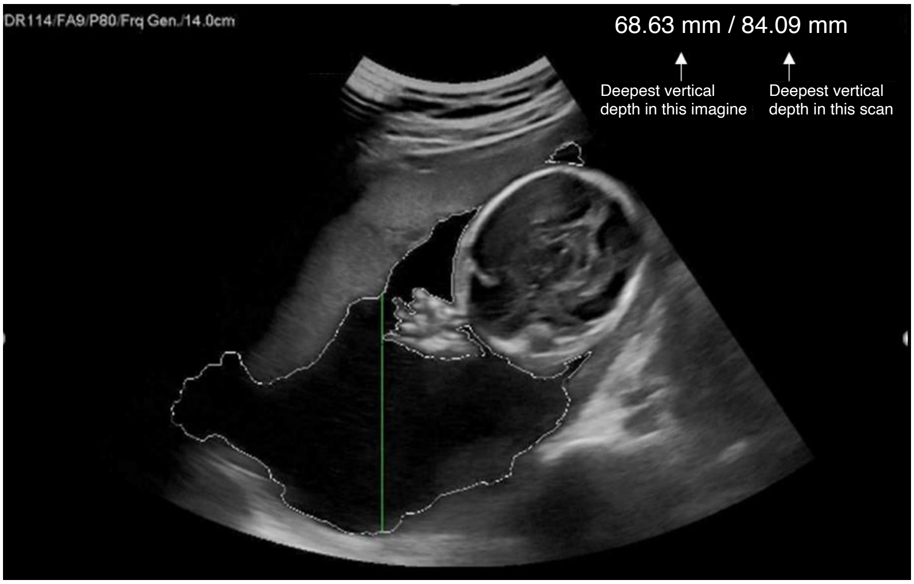

Fig. 1. **Artificial intelligence–based automatic amniotic fluid measurement program using deep learning.** The amniotic fluid part is automatically extracted from the given image and the deepest vertical depth of the amniotic fluid part; that is, the amniotic fluid index is automatically calculated.

calculation of the fetal heartbeat has been carried out in many studies that have extracted the fetal heart rate from CTG using dimensionality reduction [38,41] or measured fetal QRS complexes from maternal ECG recordings using ANN [42] and pulse-wave Doppler envelope signals extracted from B-mode videos [43]. For cases with congenital heart anomalies, an intelligent navigation method referred to as "FINE" was developed and this can detect four types of abnormalities [44]. Arnaout et al. [39] demonstrated a deep learning method identifying the five most essential views of the fetal heart and segmentation of cardiac structures. They found that hypoplastic left heart syndrome was the most frequently distinguished anomaly compared to normal structures and tetralogy of Fallot at the gestational age of 18 to 24 weeks (Table 2) [39,45]. Although progress has been made towards obtaining optimal images within a short period of time, with a minimal learning curve and extraction of standardized planes using large databases with AI technology, limitations remain in the assessment of appropriate images followed by clinical decision-making in the realm of the fetal heart compared to other organs [46]. Further studies using appropriate AI technology for different types of congenital heart diseases and with more subjects and various US machines are warranted.

Others

Estimation of gestational age [36] and prediction of preterm birth [47,48], aneuploidy [49,50], and asymptomatic short cervical length [40] have been investigated using machine learning algorithms. An effective system was developed for predicting fetal brain abnormality [51]. A recent systematic review demonstrated that a model for the prediction of prematurity using the support vector machine technique performed best among 31 studies analyzed, with an accuracy of 95.7% [52]. Deep learning-based automatic measurement programs for parameters indicating the progression of labor (e.g., the angle of progression) are currently applied. AI-based programs have advantages in terms of obtaining more objective results and may be helpful for parameters that are clinically important but may have errors between measurers. For example, measurements of amniotic fluid are susceptible to errors between measurements, which can affect treatment decisions, and AI-based programs that can automatically measure these items are being developed (Fig. 1). A recently published paper reported that an automated method based on deep learning was very useful for measuring amniotic fluid [53]. In addition, AI-based programs can be helpful for measurements that require evaluators to be fully trained and experienced, such as nuchal translucency [37,54,55], and these techniques may be combined with a robot arm that performs the scanning to automatically extract standardized fetal imaging views. Related research is actively underway, and the results are expected to be available in clinical practice in the relatively near future.

In 2020, the International Society of Ultrasound in Obstetrics and Gynecology introduced the latest research trends being developed in the field of obstetrics and gynecology through an "Artificial Intelligence in Imaging" session. The most surprising finding was that, in addition to providing the function of extracting and measuring the desired organ or part after analyzing data within a given image (as discussed above), systems have been developed that suggest a suspected diagnosis based on the measured values. The day is not far away in the future, when an ultrasound probe placed on a mother's abdomen will not only measure basic parameters, but also provide related diagnoses and further treatment directions.

Magnetic Resonance Imaging

MRI is being actively studied along with US. In the obstetric field, MRI is usually performed to discriminate fetal brain diseases and the severity of placenta previa. In one study, the brain structure of the fetus was automatically extracted and analyzed through MRI scans of 45 pregnant women, and furthermore, the volume was automatically measured [56]. In another study, through the analysis of 59 MRI scans with fetal ventriculomegaly through various AI techniques, the need for additional treatment required after birth, such as cerebrospinal fluid diversion, was predicted with 91% accuracy [57]. In other words, AI can provide information on whether related treatments are needed along with a diagnosis using MRI scans. In addition, MRI applications related to the placenta have been widely studied. The presence of placenta adhesions was diagnosed with 100% sensitivity, 88.8% specificity, and 95% accuracy by applying AI techniques through MRI scans of 99 pregnant women diagnosed with placenta previa [58]. MRI scans of 44 pregnant women, including those with twins, were used to accurately measure the volume of the placenta and the distribution of vessels on the surface of the placenta [59]. These results will provide important information for understanding and treating twin-to-twin transfusion syndrome.

Conclusion

AI is no longer a temporary social phenomenon or a topic only for specific scientific fields. Instead, it is a technical field that can help in improving diagnosis, treatment strategy, and clinical outcomes and overcoming various problems related to diagnosis even in the obstetric field. It would not be an exaggeration to say that it already occupies an important position in our field of care. Using AI methods in medical care could facilitate individual pregnancy management and improve public health, especially in low- and middle-income countries. In the future, various efforts will be required for different applications in obstetrics, and above all, the generation of data for the development of appropriate models and algorithms in various fields will be of paramount importance. Further studies need to be done to reduce bias when creating algorithms and to increase adaptability in the system, enabling the incorporation of new medical knowledge as new technology surfaces. The authors look forward to ongoing developments in AI applications for obstetrics, and above all, it is emphasized once again that AI technology is not a substitute for medical staff, but plays the role of an assistant in medical practice.

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Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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