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ARTIFICIAL INTELLIGENCE IN OBSTETRICS: THE JOURNEY SO FAR

Obstetrics & Gynaecology

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ABSTRACT

Artificial intelligence (AI), is a mathematical algorithm based digital computer system, which mimics human cognitive functions of learning and decision making. AI has been applied in multiple fields of healthcare as a promising tool to help clinicians in daily clinical activity, not only in assisting in disease prediction, prevention, and diagnosis, but also in monitoring the disease. The accuracy of prediction depends on the algorithm and the data. In obstetrics, AI has been actively applied in different areas, e.g., for prenatal diagnosis, fetal heart monitoring, prediction and management of pregnancy related complications (e.g., preeclampsia, preterm birth, gestational diabetes mellitus, and placenta accreta spectrum), and labor management. AI uses automated tools that define what is normal or abnormal & help predicting complications. This write up provides an overview of use of AI in different areas in obstetrics.

KEYWORDS

Artificial Intelligence, Obstetrics, Prediction of Complications, Fetal Heart Monitoring.

AI or the manmade thinking power, is a digital computer system, which can develop intelligent machines, which are able to make decisions by behaving and thinking like humans, and have skills like learning, reasoning and problem solving. While computer is a preprogramed machine, AI is machine with programmed algorithms which can work with its own intelligence.

The idea of "a machine that thinks" dates back to ancient Greece, but AI has evolved fast with the advent of electronic computing. Alan Turning published the paper "Computer Machinery and Intelligence" in the year 1950, though the word AI was coined in 1956 by John Mc Carthy. First computer based on neural network that learned by itself, was built by Frank Rosemblatt in the year 1967. The year 1997 was marked in history of AI, when IBM's" Deep Blue" beat the world chess champion Garry Kasparov. In 2023, there was a rise in large language models or LLMs, such as chat GPT, and with their new generation AI practices, deep learning modules were developed that can be pretrained on vast amount of raw unlabelled data, to learn a predefined skill.[1]

AI can be of three types, Artificial Narrow Intelligence (ANI), also know of weak AI, which can perform specific tasks which are below the level of a human brain and lacks general cognitive abilities. e.g., Apple Siri, Google assistance, playing chess and self-driving car. Second is Artificial General Intelligence (AGI) or strong AI, which is capable of performing tasks at the level of human brain i.e., being capable of understanding, learning and applying knowledge. Currently no such system exists and is under research. The third one is Artificial Super intelligence (ASI), a hypothetical AI surpassing human intelligence, which can perform tasks exceeding the level of a human brain, at present it exists in science fictions only.

Various technologies used in AI are Machine Learning (ML), Natural Language Processing (NLP), Computer vision, Robotics and speech recognition etc. In healthcare, mainly ML is used which involves algorithms that enable machines to learn from data and improve their performance without explicit programming.

ML is commonly subdivided into-
i. Surpassed learning: – Where target levels are defined in advance e.g., prediction of surgical site infection rates by providing data on patient's characteristics and variables correlating with infections.
ii. Unsurpassed learning: - Where target labels are not defined and used for clustering e.g., to categorise by ultrasound examination by normal or abnormal images. It uses deep learning techniques to build a model that learns different features of images to recognize different patterns.
iii. Reinforcement learning: - Describes a repetitious process of the machine learning from past mistakes i.e., learning based on feedback or reward.

Deep learning (DL) is a subset of ML, where artificial neural network mimics the human brain's ability to make automatic predictions from training data sets using numerous layers of artificial neural networks. Deep learning needs a significant quantity of data and a long training and higher accuracy and it learns by itself from expenses and prior failure.

AI is transforming industries around the world, and as the year 2024 begins, its application is rapidly increasing in the healthcare sector too. AI is used in various areas of healthcare such as disease diagnosis, drug research patient monitoring etc. It helps to gather past data through electronic health records for disease prevention and diagnosis. Various AI algorithms are also being developed for the healthcare industry that help to support operational initiatives that increase cost saving, improve patient satisfaction and satisfy their workforce needs.

The development of MYCIN in the 1970s is one of the earliest examples of AI in medicine, developed by a team at Stanford University led by Edward Shortliffe, which was a computer program that could diagnose bacterial infections and recommend appropriate antibiotic treatments. Another example is AI-based expert system such as DXplain, developed at Massachusetts General Hospital in 1980s, & was used to assist the diagnosis of diseases. These early AI systems were rule-based systems and had limited capabilities. [2]

In obstetrics, AI is being increasingly used for early detection of anomalies, prediction of possible pregnancy related risks, enhancing fetal monitoring and timely intervention to improve both maternal and neonatal outcomes. One of the primary areas in which AI and ML are being used in obstetrics and gynaecology is in the analysis of imaging data, such as ultrasound and magnetic resonance imaging. AI algorithms can be trained to automatically identify and classify different structures in the images, such as the placenta or fetal organs, with high accuracy. The development of computer-aided diagnostic systems for ultrasound images in the 1970s and 1980s are one of the earliest examples of use of AI in obstetrics. With the advances in ML and the availability of large amounts of data in recent years, there has been a renewed interest in the use of AI in obstetrics and gynaecology.

Obstetrics Ultrasound

Fetal ultrasound diagnosis is dependent on the operator's experience, ultrasound machine's performance, and there are many maternal or fetal factors that can negatively influence the diagnostic reliability, eg, maternal obesity and unfavorable fetal position. AI, through deep learning techniques, has significantly improved the quality and accuracy of ultrasound imaging in obstetrics, providing clearer images of the fetus and maternal organs. This allows early detection of anomalies and better assessment of fetal growth, for example the accurate estimation of gestational age, diagnosis and monitoring of fetal growth restriction, accurate and timely diagnosis of anatomic malformation and classifying a full fetal echocardiogram. [3]

Smartplanes, a software for fetal biometry, has been used by Grandjean et al that is able to automatically identify the transthalamic plane from 3D ultrasound volumes and measure the BPD and HC accurately.[4] Wu designed the Artificial bee colony algorithm, which processed the Doppler ultrasound images that could greatly enhance the ultrasound images quality, decreases the noise of images, and highly improvise the capability of clinical diagnoses of the disease in different pregnancy phases, up to the birth of a child.[5]

During pregnancy, the placental images of patients having hypertension, deviate from those populations without hypertension. AI is utilised to assess the variations in the placental ultrasound image texture of pregnant women with hypertension, and the data is used to develop a textural feature extractor module, which could be used to predict hypertensive disorders of pregnancy (HDP), which can also estimate adverse pregnancy outputs before the clinical manifestation of the disease.[6]

Fetal cardiac ultrasound screening generally possesses a low rate of detection of congenital heart disease because of difficulty in mastering the technique by traditional ultrasound, but a novel DL-based system is developed by Sakai et al., by which the screening performance of congenital heart disease in the second and third trimesters improved significantly.[7] A fully convolutional DL method is used by Arnaout et al to automatically obtain 5 different views of the heart and measure cardiac structure.[8]

To screen for any malformations of the congenital central nervous system (CNS) during pregnancy, AI conduct system, PAICS is proposed to determine various fetal intracranial abnormality patterns in standardized sonographic reference.[9] Similarly, Burgos-Artizzu et al. assessed the performance of the AI method based on automated analysis of fetal-brain morphology of fetus upon standard cranial ultrasound section for predicting the gestational age parameters in II and III trimesters of pregnancy. The comparative assessment is explored by comparing with present formulas through standardized fetal biometry.[10] Rizzo et al. assessed the performance of a software called 5D CNS to measure all CNS parameters, e.g., posterior ventricle, transverse cerebellar diameter, and cisterna magna, in a 3-dimensional volume of the brain in second trimester scans, with a good degree of reliability between 2D and 5D measurements for both BPD and HC. This system reduces the waste of time related to fetal position and operators' expertise in 2D-ultrasound. [11,12] A model called View-based Projecton Networks was proposed by Huang et al. to identify multiple brain structures using 3D neurosonography, similarly, Namburete et al. described an automated system to predict gestational age and brain maturation by capturing 3D volume neurodevelopment image signatures.[13,14]

Prenatal diagnosis of fetal aneuploidies is based on invasive diagnostic tests and noninvasive screening tests. Nowadays, the most common screening tests are first trimester combined screening and cell-free fetal DNA testing. Efforts to apply artificial intelligence algorithms to prenatal genetic diagnoses have long been made and have shown good results Neocleous et al. reported a computational intelligent approach for a noninvasive estimation of the risk of aneuploidies with good results. [15-18] A similar approach based on ANNs was proposed by Catic et al. for automatically identifying 5 different types of chromosomal abnormalities. Yang et al. Troisi et al. have created an ML model based on maternal serum metabolomics fingerprint of fetal chromosomal aneuploidies during the second trimester of pregnancy, which can be a useful tool in differentiating among normal and abnormal fetuses. [19-24]

Fetal Heart Monitoring and Interpretation

Continuous fetal heart rate monitoring is widely used to monitor fetal heart rate and uterine contraction as a means of detecting fetal distress. Fetal heart rate monitoring leads to a decrease in birth asphyxia and its complications, however, it is associated with an increase in C-sections and instrumental vaginal birth rates the interpretation of CTG and fetal physiology could be facilitated through AI, limiting the adverse impacts of its misinterpretations and human errors due to higher intraobserver and interobserver variability. AI based recommendations especially those generated via deep learning models have optimal results that interpret the findings that may not be visible to eyes and can predict fetal distress with novel patterns of abnormalities.

There are reports of successful abnormal fetal heart rate pattern and fetal electrocardiogram prediction using deep learning, though the INFANT study did not show difference in maternal and neonatal outcomes between those given the adjunctive clinical decision support via this system & those without it.[25, 26] The OxSys system, a model based on multimedia convolutional neural network, which can identify novel findings, such as decelerative capacity has shown more promise and CTG Net, a system which identifies normal pattern, as well as allows contracted based monitoring, has been found to deliver good performance in terms of the automatic analysis of FHR based on cardiotocograph data. It promises to be a key component of smart obstetrics systems of the future.[27,28]

Prediction Of Risk For Adverse Outcomes

Clinical data has been widely used by obstetricians to identify the patients at risk of adverse perinatal outcomes. AI predictive models using machine learning has been developed to predict a range of pregnancy related abnormalities including preeclampsia, shoulder dystocia, PPH & even postpartum depression. AI predictive modelling using natural language processing can even decide the optional mode of delivery.[3] AI models can track physiological measures like body temperature, heart rate variability, blood pressure, and other behavioural measures such as quality of sleep, sleep duration and the relative activity of patients. Tracking of these physiological parameters have benefits in determining risks of conditions like gestational hypertension and preeclampsia.

AI could be a prominent tool to generate algorithms to identify asymptomatic women with shorter cervical lengths (CLs) who are at preterm birth (PTB) risk. In addition, the vast AI storage capacity could support the determination of preterm labor risk factors through extensive genomic data and multiomics, thereby reducing pregnancy related complications.[29] For the early diagnosis of preterm birth, the performance measures of the artificial neural network and the random forest are reported to be similar to or better than those of traditional approaches. [30]

A recent study used machine learning and ultrasound measures for the prediction of estimated fetal weight & also for the prediction of gestational weeks. [31,32] Furthermore, two recent studies involved the combination of machine learning and ultrasound measures to predict intrauterine growth restriction. So AI can be an effective non-invasive tool, together with clinical and sonographic markers, to predict intrauterine growth restriction. The most recent was the first machine-learning study for the prediction of new-born's body mass index from 64 ultrasound- maternal-delivery variables. There has also been a recent study for applying machine learning models to clinical and laboratory features of women with intrahepatic cholestasis of pregnancy to create algorithms for identifying patients without bile acid measurements. [33,34]

The applicability of machine learning models also appears to be high in predicting successful vaginal delivery. Machine learning algorithm for TOLAC (The trial of labor after caesarean selection) analysed with 989 cases demonstrated more accurate predictive power than conventional maternal–fetal medicine units calculator. [35] Moreover, AI algorithms can also predict the risk of stillbirth giving invaluable information for patient care. Shoulder dystocia must be the least accessible clinical situation for obstetricians. A recent study presents a good model for predicting shoulder dystocia using machine learning & was found to be of significantly better predictive power than current clinical guidance based on fetal weight and gestational diabetes. [36]

Postpartum complications are difficult to predict and, if they actually occur, these place a heavy medical and socioeconomic burden on mothers and their families. AI systems could play an important role in determining the risk of postpartum complications in advance. [37]

AI models have been developed which can analyse physiological and clinical data to predict the labor onset, crucial for timely hospital admission and intervention. improving hospital resource management and reducing the risk of complications during childbirth.

Remote Monitoring And Telemedicine

One of the major utilisations of AI integration in areas of low resource will be remote monitoring and telemedicine solutions providing comprehensive care to patients in rural or underserved areas. Regular check-ups and consultations during pregnancies can be provided through video conferencing, reducing the need for physical visits. AI-enabled monitoring devices can also transmit real-time data, like blood pressure and heart rate of the patient, and fetal heart rate of fetus, allowing for timely interventions and support.Challenges Of the Artificial Intelligence.

The main advantages of use of AI are related to the reduction of inter and intraoperator variability, reduction of length of procedures, and improvement of overall diagnostic performance of obstetrics and gynaecology conditions. Despite its advantages, there are several limitations and challenges of use of AI in medicine.

AI predictive models require large amounts of data to be effectively trained and tested, and accurate models cannot be developed if available data is limited. Developed AI models can have a certain population or group bias, depending on the training provided. The scarcity of data can lead to AI models that are not generalisable to certain populations or that make incorrect predictions for certain groups of patients. When applying AI in clinical practice, another factor to consider is its applicability. Non-mentioned clinical data are ignored by the AI model because AI models can only account for data that have seen during training.

There will always be a trust issues in prediction models as it can be difficult to understand how they arrived at a particular decision or prediction. In situations where there is a lot of uncertainty or multiple outcomes are possible, AI models can struggle to make predictions, particularly where diagnoses are based on patterns and symptoms.

There are also ethical concerns surrounding the use of AI in medicine, such as the potential for discrimination or the replacement of human doctors with AI systems. In contrast to human writing, AI-generated content is more likely to be of limited depth, contain factual errors, fabricated references and repeat the instructions used to seed the output. Privacy and data security concerns are always there and must be addressed to protect patients' sensitive medical information.

CONCLUSION

AI is fast emerging as a powerful tool in all the fields of medicine, revolutionising the approach of healthcare professionals to diagnose & manage the patients. Computerised algorithms have made the predictions simple and accurate, helping clinicians in managing cases by creating a standardized assessment to replace subjective interpretations.

Since maternal-fetal medicine deals with two lives, the mother and the fetus, stricter ethical standards will be needed for the application of AI technologies. There has to be more reliable and transparent integration of generative AI and refined LLM models ensuring clinical accuracy and patient safety, minimizing the risk of medical errors and medicolegal issues and improving management of complex obstetrical conditions. Moreover, better training of clinicians to use these systems should be ensured, AI and machine learning will not put health professionals out of business rather it is a complementary tool to the obstetrician's practice, making their job better and leaving time for more human–human interactions making the medical profession all the more rewarding.

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