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Artificial intelligence-aided decision support in paediatrics clinical diagnosis: development and future prospects

Yawen Li[1], Tiannan Zhang[2], Yushan Yang[3] and Yuchen Gao[4]

Abstract

Artificial intelligence (AI)-aided decision support has developed rapidly to meet the needs for effective analysis of substantial data sets from electronic medical records and medical images generated daily, and computer-assisted intelligent drug design. In clinical practice, paediatricians make medical decisions after obtaining a large amount of information about symptoms, physical examinations, laboratory test indicators, special examinations and treatments. This information is used in combination with paediatricians' knowledge and experience to form the basis of clinical decisions. This diagnosis and therapeutic strategy development based on large amounts of information storage can be applied to both large clinical databases and data for individual patients. To date, AI applications have been of great value in intelligent diagnosis and treatment, intelligent image recognition, research and development of intelligent drugs and intelligent health management. This review aims to summarize recent advances in the research and clinical use of AI in paediatrics.

Keywords

Artificial intelligence, paediatrics, clinical diagnosis, decision making, medical imaging, electronic health record, machine learning

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[1]School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing, China
[2]Department of Pediatrics, Peking Union Medical College Hospital, Chinese Academy of Medical Sciences, Beijing, China
[3]School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing, China
[4]School of Economics and Management, Tsinghua University, Beijing, China

Corresponding author:
Yuchen Gao, School of Economics and Management, Tsinghua University, Haidian District, Beijing 100084, China.
Email: gaoych@sem.tsinghua.edu.cn

Introduction

Artificial intelligence (AI) has developed rapidly owing to its broad application to many fields, such as clinical medicine. Paediatric clinical diagnosis, an important part of clinical medicine, has benefited much from AI in various ways.

In this study, we searched influential journals to identify and review the latest articles on AI applications in the field of paediatric clinical diagnosis. After identifying several cutting-edge applications, we categorized them into the following segmentation scenarios: physical examination, medical imaging, comprehensive analysis and diagnosis, and the use of electronic health record (EHR) systems. This review summarizes recent advances in paediatric clinical diagnosis and provides researchers with information about the future prospects of AI in paediatrics.

Artificial intelligence-assisted auscultation

During the basic process of clinical diagnosis and treatment, doctors gradually collect patient information.[1] This is combined with their own knowledge to make decisions about the next clinical stage, and is a process based on analysis and comparison.

Physical examination is one of the most effective methods by which doctors obtain patient information using simple and standard skills. However, the doctor's judgment about positive signs can be affected by the particular situation, sensory abilities and practical experience, and sometimes leads to misjudgement. For example, heart murmurs are important in the diagnosis of congenital valvular heart disease and a variety of congenital heart diseases. However, simple physiological murmurs in children and young people are common, making it difficult to distinguish pathological murmurs. Although experienced paediatricians can use simple stethoscopes to identify pathological murmurs with sensitivity and specificity of more than 90%, it is more difficult for young paediatricians and primary care practitioners to rely solely on auscultation to identify cardiac murmurs, which makes it increasingly difficult to screen for heart diseases using physical examinations.[2] Artificial intelligence-assisted auscultation (AIAA) is designed to improve screening validity. However, despite advances in heart sound classification algorithms and signal processing, this technology has not been widely adopted in clinical practice.

Clinical experiments involving noise detection algorithms are needed to compare performance with traditional auscultation and other algorithms, and to increase understanding of the potential of AIAA in clinical paediatric practice.[3] The Cardiac Auscultation Record Card (CARD) database at the Johns Hopkins Children's Medical Center contains a large amount of data from cases with pathological murmurs and with no murmurs, as well as noise-free cardiac auscultation data. Several test algorithms have been developed based on this auscultation database, and 3180 records of heart murmur cases have been analysed using an automated batch protocol. This AIAA system has been tested for measurement accuracy, patient age, heart rate, noise intensity, chest recording position and various pathological diagnostic criteria. The results show that the sensitivity and specificity of the AI system for identifying pathological cases is 93% and 81%, respectively.[4]

AI-based noise detection algorithms have been evaluated objectively and comprehensively in paediatric clinics, and have been found to operate well in clinical experiments.[5] This approach could be used to compare the efficiency of other algorithms with the same data sets, which could increase understanding of the potential clinical applications of AIAA.

Automated image-based bilirubin analysis

Automated image-based bilirubin (AIB) has been used to monitor neonatal and infant jaundice. Xuzhou Affiliated Hospital of Southeast University, China, conducted a prospective study of 194 cases of neonatal jaundice. Data on total serum bilirubin (TSB) level, transcutaneous bilirubin (TCB) concentration, AIB and clinical signs were collected when newborns were admitted to hospital, and before and after phototherapy.[6] The results showed a correlation between AIB and TSB ($r = 0.824$), with a high level of consistency (96.5% of the sample fell within the 95% limits of agreement). Furthermore, the strongest correlation and greatest consistency were found for a subgroup of newborns with TSB > 10 mg/dl and ≤ 20 mg/dl. In 97.5% neonates, TSB indicated jaundice levels lower than AIB plus 3.80 mg/dl. The main advantages of AIB are that it does not rely on the exclusive detection of bilirubin level, is non-invasive and is inexpensive. However, external environmental factors, such as insufficient light, light reflection from colorimetric cards and trembling in child patients, have a much greater impact on AIB than on TCB. These methods have a range of potential applications for family use and dynamic monitoring of moderate neonatal and infant jaundice, but comprehensive understanding of their diagnostic significance for neonatal jaundice requires further multicentre studies involving detailed evaluation.[6]

AI-based analysis of medical imaging

In addition to physical examinations, medical imaging (an important auxiliary examination method) can provide disease information.[7] Medical images, such as X-ray images, computed tomography images, pathological images and ophthalmoscope images, can play an important role in disease diagnosis. The use and analysis of medical images is another important application of AI.[8] Deep neural networks, which aim to identify the rules, modes and hidden relationships in data, have been used for image analysis.[9] Bone age radiography is commonly used in paediatric departments and enables paediatricians to estimate children's skeletal development using X-ray photographs. An AI model that includes 12,611 paediatric skeletal radiographs has been established based on machine learning and deep neural networks developed by the US National Institutes of Health. The clinical testing interpretations of four senior imaging specialists were used as a control. The root mean square of the interpretation differences for bone age in the AI model was 0.93 to 1.17 years. In terms of the stability of duplicated diagnoses, the specialists' diagnosis discrepancy rate was 14% to 18.5%, and the error rate of the AI model was 15%. The authors concluded that their deep neural networks could estimate the rate of skeletal maturity with an accuracy similar to that obtained by radiologists and existing automated methods.[10] AI-assisted image technology, such as computed tomography and magnetic resonance imaging, is one of the 30 most rapidly developing domains in cancer research.[11] In addition, one review of AI applications for depression found that papers on electroencephalography-based diagnosis accounted for the largest percentage of publications reviewed.[12]

AI-based comprehensive analysis of multiple information

The diseases mentioned above can be clearly diagnosed from specific signs and typical imaging information. However, some diseases must be diagnosed through comprehensive analysis of multiple information sources, such as patient signs, symptoms, test results, radiological images and therapeutic responses. Each patient is unique and shows different symptoms. It is important for doctors to consider whether results are consistent with the patient's self-reports. However, it is inevitable that doctors will occasionally make diagnostic mistakes in the course of their careers. Many factors can lead to such mistakes, including doctors' knowledge, experience and psychological and emotional states. One machine-learning approach, the multilayer perceptron method, can handle the complicated properties of different types of data.[13] The application of AI to diabetes diagnosis is attracting much interest.[14] This requires the comprehensive analysis of several parameters that include heart rate variability and arterial blood glucose alterations. A machine-learning algorithm has been designed to dichotomize subjects as diabetic or non-diabetic.[15]

Artificial intelligence and electronic health records

The adoption and use of EHR systems is considered an integral part of solving the problem of medical errors. The rapid development of EHR systems has presented the challenge of AI management of large amounts of data and text information.[16] The use of EHR systems ensures that reliable information about different patients is integrated and utilized in patient care, and promotes automated error detection and clinical diagnosis.[17]

Machine learning can provide objective, comprehensive and accurate results from database analysis.[18] The application of machine learning in EHR is of great value. First, predictive modelling with EHR data can save labour, enhance efficiency, increase accuracy[19,20] and promote personalized medicine.[21] Second, machine-learning techniques can transform a large amount of textual information and unstructured data from patient records into structured data.[22,23]

Summary

Owing to the large age range and substantial individual differences among paediatric patients, paediatric EHR data often lacks wide coverage and has a high distribution imbalance.[24] In addition, expert diagnosis may be affected by subjective factors such as fatigue level and diagnosis time limits.[25] AI-assisted diagnosis is essential to provide complex diagnostic mechanisms and to increase the efficiency and accuracy of paediatric clinical diagnostic services.

In China, the application of AI in paediatric clinical diagnosis has mainly focused on accurate diagnosis and treatment, medical image recognition, intelligent health management and patient triage. These applications feature an increasing number of approaches. Future potential applications include classification of disease diagnosis, individualized treatment guidance, prognostic evaluation and clinical studies enrolment.

Although AI has shown great promise in paediatrics, substantial technical barriers remain to be overcome. The scarcity of high-quality data indicates the need for joint development of a package of schemes.[26] Combined analysis using feature enrichment integrated with health informatics could strengthen training efficacy and diagnostic accuracy.

We hope that the advances summarized in this paper, and the challenges and future prospects identified, will inspire research in AI approaches for paediatrics.

Declaration of conflicting interest

The authors declare that there is no conflict of interest.

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ORCID iD

Yawen Li https://orcid.org/0000-0002-6556-2560

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