Artificial intelligence in pediatrics

Ya-Wen Li[1], Fang Liu[2], Tian-Nan Zhang[3], Fang Xu[4], Yu-Chen Gao[5], Tian Wu[6,7,8]

[1]School of Economics and Management, Beijing University of Posts and Telecommunications, Beijing 100876, China;
[2]Department of Stomatology, Beijing Children's Hospital, Capital Medical University, National Center for Children's Health, Beijing 100045, China;
[3]Department of Pediatrics, Peking Union Medical College Hospital, Chinese Academy of Medical Sciences, Beijing 100730, China;
[4]School of Banking & Finance, University of International Business and Economics, Beijing 100029, China;
[5]School of Economics and Management, Tsinghua University, Beijing 100084, China;
[6]NCMIS, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China;
[7]School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China;
[8]Key Laboratory of Big Data Mining and Knowledge Management, Chinese Academy of Sciences, Beijing 100190, China.

The rapid development of information technology has involved advances in artificial intelligence (AI), big data processing, and cloud computing, with significant and far-reaching effects on the structure and efficiency of the traditional healthcare industry, as well as the establishment and maintenance of modern medical management information systems. AI solutions for handling data in the medical field, such as electronic medical records, medical imaging technology, medical big data, intelligent drug design, and smart health management systems have emerged, which improve the standardization and accuracy of clinical decision making, while providing more dimensions of data accumulation for medical knowledge-based systems. These developments can also support physicians and researchers in the optimization of treatment plans, and decision making about optimal treatment options. This review aims to summarize recent advances in the research and clinical use of AI in pediatrics.

AI has promising applications in medical research, using clinical databases. One research group successfully identified four subtypes of sepsis from 6708 pediatric cases using natural language processing (NLP), deep auto-encoding and unsupervised clustering. Importantly, these four subtypes presented distinctive clinical features, and the testing results coincided accurately with clinical features, which enhanced the rationality and reliability of the clustering results. This model is capable of handling multiple model data lists at the same time, which not only includes structural data such as demographic characteristics and laboratory tests, but also extracts useful information from unstructured data such as medical records and image reports, whose analysis results tally with clinical retrospective research results.[1] Diagnosis of sepsis and differentiation standards are potential to be improved.[2]

Gomberg-Maitland and Souza (2017) used AI with deep machine learning to improve pediatric pulmonary hypertension (PH) and related diseases, aiming to enable earlier and more accurate diagnosis. The authors performed general analysis through comparative statistical methods and established a Bayesian research network to analyze 186 children suffering from PH and without PH. This analysis eliminates the relationship between dependence and independence, and evaluates the possibility of complications. Importantly, these techniques can be used in clinical research. In addition, the authors used AI technology such as a noisy-OR model, bootstrap modeling and network clustering, which allowed them to reduce the noise and increase the diagnostic validity. The networks were further evaluated by doctors and one investigator who reviewed the inter-rater validity and dealt with discrepancies based on the statisticians' and doctors' concerns. A literature review was conducted to analyze and evaluate the clinical reliability of the findings.[3] The AI analysis focused on pediatric PH not only verified the existing mature subtype classification system, but also identified the uncommon subtypes in only a few case studies, in accord with rare genetic syndromes, which are excluded in the system.

In investigating the relationship between brain volume overgrowth and autistic social deficits (ASDs), the

Access this article online	
Quick Response Code:	Website: www.cmj.org
	DOI: 10.1097/CM9.0000000000000563

Correspondence to: Yu-Chen Gao, School of Economics and Management, Tsinghua University, Beijing 100084, China
E-Mail: gaoych@sem.tsinghua.edu.cn

Chinese Medical Journal 2020;133(3)
Received: 09-08-2019 **Edited by:** Xiu-Yuan Hao and Xin Chen

investigators conducted a prospective study, in which 106 infants at high familial risk of ASD and 42 low-risk infants were included, using the deep-learning algorithm. Surface area information was obtained using magnetic resonance imaging of the brains of individuals at the age of 6 to 12 months old to predict the diagnostic validity of pediatric autism at 2 years. The results revealed a predictive sensitivity of 88%, with an acceptable positive predictive value.[4] Thus, the application of AI technology enabled confirmation of the relationship between early brain changes and autism-related behaviors, and is expected to support the early identification of autism.

The application of AI in neonatal daily care is also an important medical scenario, mainly for effective monitoring of newborn jaundice. An information system was established with the help of mobile phones for the purpose of monitoring newborn jaundice, and k-nearest neighbor (KNN), least angle regression (LARS), fusion of Least Absolute Shrinkage and Selection Operator (LARS-Lasso) Elastic Net, ridge regression, random forest support, and vector regression have been applied in machine learning algorithms.[5] In Aydın *et al*'s neonatal jaundice detection system, at the stage of estimating bilirubin levels, the KNN and support vector regression algorithms are used to regress the feature-extracted data sets.[6] In addition, Hao *et al* proposed an intelligent system for diagnosing newborn jaundice with a dynamic uncertain causality graph model.[7] The accelerated establishment of large amounts of healthcare data has fundamentally changed the nature of healthcare. Some researchers have applied AI in the genetic analysis of congenital cleft lip and palate, with promising progress.[8] The pediatrician-patient relationship is the cornerstone of providing medical services to children, and the involvement of AI not only improves operational efficiency, but also enriches the nature of this relationship.[9]

For diagnoses of common diseases that can benefit from many cases, engineers can accumulate data regarding symptoms, test indexes, routine care, treatments and responses, follow-up, and prognosis. Using these big data sets, a number of AI-based diagnostic models have been developed.[10,11] For example, it was reported that a diagnostic model for childhood asthma was established based on four machine learning models, three of which were found to operate effectively using pre-formed decision trees. The addition of weighting, social and economic status and weather data were found to enhance the models' performance.[12] In addition, a model of community-acquired pneumonia in children has been trained successfully to recognize various types of abnormal image retrospectively.[13] Nevertheless, only a few prospective controlled trials regard machine learning models as a part of pediatricians' routine work. At present, lack of mature AI systems for disease diagnosis remains. In the field of electronic health records, text mining is a basic technology for developing contextualized theories of effective use.[14]

At the same time, the development of AI faces several challenges, such as standardized data collection, quality management, information sharing, privacy protection, regulatory policies, and ethical considerations.[15] More AI medical models are likely to emerge in the next few years. AI-assisted laboratory testing, AI-assisted medical imaging and AI-based decision tree methods for diagnosis and management of different pediatric diseases may develop rapidly. These models, as well as the regulatory framework for value-based healthcare and the development of economic incentives are all reasons for cautious optimism about machine learning in the field of pediatrics. Regardless of how technology evolves, providing optimal management for patients is the core goal of pediatrics.

Funding

This research was funded by the National Natural Science Foundation of China (No. 61902037), the Fundamental Research Funds for the Central Universities (No. 500419804), the China Postdoctoral Science Foundation (No. 2018M641397), and the National Center for Mathematics and Interdisciplinary Sciences, CAS.

Conflicts of interest

None.

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How to cite this article: Li Y, Liu F, Zhang T, Xu F, Gao Y, Wu T. Artificial intelligence in pediatrics. Chin Med J 2020;133:358–360. doi: 10.1097/CM9.0000000000000563