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AI Assisted Clinical Diagnosis & Treatment and Development Strategy

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Abstract: The integration of healthcare data, open access to healthcare data, and use of artificial intelligence to organize and analyze fragmented medical information can improve medical and health services, promote the level of rational decision-making by the government, and reduce any inequality in the allocation of medical and health resources. This paper summarizes the current status of artificial intelligence technologies and their applications in the fields of medical information semantic fusion and image analysis. This study also analyzes the current problems and challenges associated with these technologies. First, the construction of clinical terminology standards by standardized representation and structural integration of medical information is key. Second, using medical knowledge to construct an intelligent diagnosis and treatment model with the capability to combine multimodal data analysis and structured knowledge reasoning is currently the focus of development in image intelligence. Thus, we propose a nationwide healthcare open data cloud platform that can open new data markets, improve the integration of healthcare data, and provide new services pertaining to knowledge discovery and utilization. We also suggest some basic industry standards for medical and health information to strengthen the research and development of domestic medical devices, promote the development of intelligent medical devices and smart wearable devices, and guide the industry toward new frontiers in the combination of artificial intelligence and medical devices.
Keywords: artificial intelligence; assisted diagnosis and treatment; knowledge graph; medical ontology; medical image analysis

1 Introduction

The number of patient visits in varied-level medical institutions in China has reached 7 billion per year; however, the uneven and badly mismatched distribution of medical resources has placed intense pressure on the limited number of healthcare providers. With the rapid development of health information technology, electronic medical records (EMR), and personal health records (PHR), a huge amount of multimedia information in the format of documents, forms, images, and audio have been generated. Therefore, the application of artificial intelligence (AI) technology is expected to assist clinical procedures through data integration and analysis. This will afford new opportunities to enhance the capacity and quality of healthcare, thus relieving the shortage of medical resources in China.

In July 2017, the China State Council issued a policy called the *Development Plan for the Next Generation of AI*, which mentioned that the application of AI technology in the field of intelligent healthcare should be promoted in the future. Innovative models and methods of intelligent diagnosis and treatment are encouraged in practice, as fast and accurate intelligent medical systems are expected to solve the problem of medical resource allocation. AI technology in semantic analysis, data mining, and text understanding in the massive open accessible medical

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data facilitates the automatic construction of medical semantic networks and knowledge graphs. For example, through a quick search for massive medical literature, clinical cases, and treatment protocols by computer, the implicit relationships among data could be revealed; hence, research on clinical decision support and drug research and development should be conducted to promote the advancement of medical technologies. Moreover, the intelligent analysis of medical images can accurately extract features and locate the disease focus, which provides useful support for disease prevention and diagnosis. In addition, technologies of voice recognition, video understanding, and intelligent chat bots are also expected to be applied in the fields of automatic medical record writing, nursing, rehabilitation guidance, and consultation guidance.

The capability of integrating and analyzing fragmented information is the cornerstone for supporting effective clinical diagnosis and treatment, and it relies on medical standardization to improve healthcare service quality and promote decision accuracy on medical resource allocation by governments. Standardization also plays an important role in medical AI development. This paper will focus on the medical AI field of human–machine interaction, where semantic text understanding and image analysis are the dominant factors for the application development. In addition, the current situation and future trends of AI in clinical supportive diagnosis and treatment will be briefly presented. We will also discuss the main issues and challenges present in the development and application of an intelligent medical system, with the aim of assisting governments in decision making.

2 Current semantic understanding and image analysis of medical information

Research on clinical disease diagnosis by AI technology mainly focuses on two areas: one is prompt extraction of key information from massive medical data through methods of reasoning, analysis, comparison, induction, summary, and argument to draw cognitive medical conclusions from a patient's physical condition [1,2]; the other is to conduct data mining based on multimedia clinical diagnostic data in the formats of text, audio, image, and video to support diagnosis and evaluation by distinguishing the characteristics of various diseases [3]. As such, standardized representation and structured integration of medical information are the basis for supporting diagnoses through big data intelligence approaches. In addition, as deep learning has made breakthroughs in the field of image feature extraction, medical imaging, which is the diagnostic basis reflecting the body's status, has been one of the most promising fields in AI-aided clinical diagnosis. This section summarizes current research and development of semantic understanding and image analysis of medical information, with the aim of better illustrating the current status of AI-aided clinical diagnosis and treatment.

2.1 Construction of medical knowledge graph and terminology standards

Owing to the application of health information technologies, huge amounts of medical data have been accumulated over the past decades. Structured and unified expressions of medical terminology are the basis for the adoption of AI for convenient storage and retrieval of medical information.

As semantic networks are designed to efficiently retrieve and link data from massive and fragmented information, they can well express and organize the relationships among large-scale data entities. By linking medical concepts and relationships, the semantic relationships among entities can be effectively and conceptually retrieved. Various data from medical institutions such as pharmaceutical data, clinical cases, health monitoring data, genome data, diet, and sport data from patients can be linked and documented based on a knowledge graph. This is also the basis for constructing a personalized, dynamic, multi-view, and semantically understandable clinical decision support system. Information retrieval, knowledge reasoning, and knowledge discovery can be efficiently conducted with the help of a knowledge graph. Innovative applications like patient education, supportive clinical decision making, drug research and development, and intelligent medical guidance could be introduced [4,5]. This approach can not only improve the working efficiency of the busy healthcare providers in cities, but also provide good advice for basic medical systems in rural areas.

General knowledge graphs such as Google Knowledge Graph, Yago, DBpedia, and Sogou "Knowledge Cube" have already been widely used. These large knowledge graphs are generated based on the integration of structured and semi-structured data like the "Online Encyclopedia", and are further developed through entity extraction, entity linking, relationship extraction, and attribute extraction technologies from unstructured open-access information in different sources and formats. These will be expanded and updated through knowledge fusion and knowledge verification [6].

As a vital application area, the development of knowledge graphs in medicine has always drawn worldwide attention. Through the incorporation of clear definitions of core medical concepts and authoritative descriptions into the ontology structure, medical knowledge graphs represent more convenient and efficient multi-sourced heterogeneous data integration and verification, semantic web development, clinical data tagging, storing, retrieval, and aggregation of medical data. Yale University has integrated the neuroscience knowledge base SenseLab to construct the knowledge graph of brain science, from microscopic molecular to macroscopic behavioral levels [7]. It could help computers understand and express the correlation of massive information in neuroscience. The ontology-based medical knowledge database Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT) by SNOMED INTERNATIONAL (formerly named the International Health Terminology Standards Development Organization, IHTSDO) contains more than 310 thousand medical concepts with specific codes and more than 1.36 million relationships among the concepts [8]. It has been widely used in the fields of EMR, gene database construction, lab results reporting, and computer-aided input of physician medical advice. The Unified Medical Language System (UMLS), developed by the American National Library of Medicine (NLM), has integrated more than 100 controlled vocabulary databases and classification systems, comprising over 1 million concepts in biomedicine and over 5 million concepts in total [9]. UMLS connects different vocabularies in different fields into one cross-language and cross-domain tool. UMLS has been widely used in the areas of information retrieval and natural language processing. It is gradually becoming the standard in EMR and health informatics.

Research on medical terminology in China started late. Until now, no complete and widely used terminology standard has been formed. The Traditional Chinese Medical Language System (TCMLS), developed by the Institute of Information on Traditional Chinese Medicine, China Academy of Chinese Medical Sciences (CACMS), is a large knowledge graph of traditional Chinese medicine, containing over 120 thousand concepts, 600 thousand terms, and 1.27 million semantic relationships [10]. However, some limitations still exist in the construction. Its ambiguous concept definition and arbitrary relationship linking have resulted in limited industry application. In addition, the NGO of China Open Medical and Healthcare Alliance (OMAHA) has initiated a program to standardize health information through the mechanism of industry collaboration and open-sourcing. In May 2017, OMAHA launched a collaborative program with the aim of developing an open Chinese medical terminology repository through the approach of industry crowd-sourcing.

2.2 AI-aided analysis of medical images

Traditional medical image research based on machine learning mostly focused on the image features specified by physicians. As only specific features were evaluated, the generalization capability of the model is always weak. Therefore, it is difficult for the model to distinguish disease progression. However, the application of deep learning models could assist in obtaining a better capability for extracting image features that are difficult to distinguish and which are easily ignored by doctors. These features can be accurately extracted and effectively analyzed by deep learning models.

AI Medical imaging research has been applied to various types of medical images, including CT, MRI, X-ray, ultrasound, endoscopy, and pathological sections on lung, breast, skin, brain, and fundus lesions. The accuracy of artificial intelligent systems in the diagnosis of some specific diseases is higher that of most professionals.

Diabetic retinopathy is a typical symptom of diabetes. The Google DeepMind Health team has applied deep learning to solve the problem of diabetic retinopathy classification. The degree of diabetic macular edema can be graded precisely by detecting the retinal fundus images. Based on this, early alert and diagnosis of patients could be achieved. The research team collected 128 thousand retinal fundus images for the deep learning model's training. In the research, the sensitivity reached 97.5% and the specificity reached 93.4%. The accuracy rate of the detection model is almost comparable to that of a professional physician.

In China, research on medical imaging analysis based on AI technology has also made some valuable contributions. An AI diagnosis platform developed by one ophthalmology center was able to detect congenital cataract(s) by deep learning [11]. This platform could evaluate the risk of congenital cataract through the indicators of opaque areas, depth, and position of the lens, and the evaluation outcomes could be used for reference by clinical physicians in decision support. In the outcome of the research, the diagnostic accuracy rate of congenital cataract reached 98.87% and the accuracy rates of three indicators, which are opaque areas, depth, and position, were 93.98%, 95.06%, and 95.12%, respectively. In terms of decision support for physicians, the accuracy reached 97.56%.

Deep learning-based medical imaging analysis can well extract image features to identify lesion areas and classify disease types. Although the accuracy of this technology has been higher than that of traditional methods, the result still lacks reasonable explanation and supporting rationale toward the outcome. As there remains a gap during the integration of the outcome by the AI system and the physician's mindset, it is relatively difficult for the technology to be used in practice. Research on medical imaging is recommended in combination with visual perception and other technologies, so that conclusions that fit the logical thinking of a human can be drawn [12].

Some researchers have already been trying to solve the problem of interpretability of the model. The deep convolution neural network model CheXNet by Stanford University successfully explained the diagnosis outcome of pneumonia using X-rays by measuring the weight of each feature of pneumonitis in an X-ray image. A DenseNet neural network model has been used to assess the features in X-rays to obtain a higher accuracy rate than physicians, on average. Moreover, this model calculates the sum of the weight values of all the features at each pixel to evaluate the effect of these image locations during the decision-making process, and then helps physicians to understand patients' conditions based on the above explanation. As another example, the multi-tasking collaboration framework proposed by Professor Xing Bo's team, from Carnegie Mellon University, was able to precisely locate the abnormal area in a medical image through the technology of a collaborative attention mechanism. In addition to tagging for image description, the framework also automatically outputs long text reports of medical images by using the hierarchical long- and short-term memory (LSTM) model, which could well interpret the decision-making process by the system [13].

In addition to the method of extracting features in medical images to predict and diagnose diseases, building 3D models of human bodies based on medical images could also help microdevices, such as endoscopic robots, to locate and identify body lesions [14,15], which provide alternative approaches to collecting medical data from devices. Another hot research topic in medical imaging analysis is to extract image features by unsupervised learning, which depends less on data annotation and presents better results of imaging analysis [16]. Despite the fact that the current research on medical image analysis is completely dependent on image data, one trend of future development will be utilizing mass medical knowledge bases to build a comprehensive intelligent diagnosis and treatment model, which should combine well with multi-modal data analysis and structural knowledge reasoning.

3 Difficulties and challenges in AI-aided medical decision support systems in China

3.1 Unbalanced development of medical informatizaton

As data-driven technology, a big-data system with complete contents and a unified structure can not only facilitate the development of informatics in medicine but also promote the acceptance and clinical application of AI decision support in the diagnosis and treatment process.

In recent years, China has made great efforts to comprehensively improve the level of medical informatization. Since 2010, the China Ministry of Finance has funded several projects for the regional construction of medical informatization and cross-regional health information platforms. As a result, the regional medical informatization has reached a good level, and digital infrastructures have been broadly constructed. Provincial and municipal hospitals have achieved comprehensive information management. However, there remain many problems with innovative AI-assisted diagnosis and treatment systems. On the one hand, the development of medical informatization varies greatly across different regions and medical institutions, resulting in limited popularization of the mindset for solving medical problems by means of informatization. On the other hand, the medical information platforms from different institutions lack synergy; there is no aligned information exchange interface between different platforms and system versions. As a result, the information exchange between institutions cannot be smooth, leading to the failure in forming sustainable and unified data management mechanisms. In addition, further application of AI technology is also restricted by the production process and quality control of medical information. To develop shared large-scale open medical databases with high quality and a unified structure for intelligent clinical decision support of specific diseases, new drug research and development and public health decisions are an urgent yet necessary long-term task. It is recommended that a nationwide cloud-based big-data medical platform be constructed to free the data market, i.e., to develop detailed rules and standards for individual access to personal medical data, hospital healthcare procedures, payment methods and charges, patient engagement with various personal health record applications, and data transactions, which will promote the development of the medical data market and open up new markets for information integration, knowledge discovery, and healthcare services.

3.2 Limited research engagement of clinical professionals

The input from experienced doctors and medical experts is quite critical for both the development of a standardized medical information system and a high-quality knowledge graph, and the design of supportive diagnosis and treatment systems, because both authoritative medical knowledge and rich clinical experience are essential. However, owing to the imbalance between the large population and limited medical resources, physicians in China are always too busy with clinical work to devote efforts to research in AI despite any belief that intelligent technologies could relieve workloads. As such, collaborative organization in overlapping fields and incentive mechanisms are required to improve the promotion of rapid development of AI applications in medicine. Alternative approaches include setting up relevant innovation centers, deploying innovative science and technology plans, and conducting effective strategies of industry-university-research collaborations.

3.3 Incompact AI integration with medical devices

In the field of medical devices, China has little innovation or core technology. The domestic industry structure is currently low-end product oriented, with main parts of the products being highly dependent on import, and high-end products are mostly imitated [17]. Due to the lack of independent intellectual property, the application of AI technology is difficult in these high-end medical devices, resulting in increased difficulties toward building an integrated medical information system for information collection, analysis, processing, and storage. In addition, the high cost of the imported devices also constrains their deep application in primary care in China, which is also one of the key factors affecting the promotion of AI systems in the primary market, thus restricting the upgrade and transition of China's healthcare industry. Under such circumstances, we need to develop specific strategies to stimulate local innovation in this field, and encourage domestic enterprises to purchase first-tier medical device manufacturers abroad. It is recommended that the government offer favorable policies in taxation, approval, subsidies, and hospital procurement toward domestic medical device companies with AI technologies to help China become a leader in the innovation market.

4 Recommendations on future development of AI-aided clinical support decisions

4.1 Building an open and shared healthcare information environment

As supportive diagnosis and treatment systems under AI are based on big data, the critical issue of medical data fragmentation needs to be solved, and the gaps among data, knowledge, and intelligence must be filled in. Connecting isolated data islands and setting up interdisciplinary medical knowledge centers for individuals and medical institutions will be beneficial toward building an open and interconnected information sharing environment.

First, it is critical to develop a unified Chinese medical term repository. Unified and sophisticated descriptions or coding rules for medical terms should be established, and an organization for continuous terminology maintenance should be intensively supported.

Second, open infrastructures enabling integration of data from various sources and of different types should be constructed. The development of knowledge graphs for various medical disciplines, fields, medical institutions, and detailed applications should all follow the unified standard. We need to increase the digitization level of Chinese medical systems to further promote the medical semantic network. Based on these, tools for medical concept searching and document retrieval can be developed to provide more authoritative and accurate information search channels for medical applications.

Lastly, an open platform for healthcare big data sharing should be set up. Health information from various sources, including medical institutions and public health service organizations, should be uniformly managed under the open platform to achieve the objectives of high data integration and interchange of personal health records, biological samples, gene sequences, medical records, behavioral patterns, and even data regarding living environments. In addition to the open platform development, existing medical information platforms should be adapted in accordance with standards; therefore, data specifications need to be applied to achieve unified information storage, expression, and transmission across different subjects.

4.2 Establishing an innovation mechanism for man-machine integration

The role of AI is to build a new approach to medical treatment based on man–machine collaboration that combines biological intelligence with AI capabilities, rather than replacing physicians. The objective is to update the knowledge of AI systems by cognitive model development and to improve the knowledge accumulation and understanding of humans.

In the medical device industry, research and development of local high-end medical devices should be strengthened; meanwhile innovation in intelligent medical devices and smart wearable devices should also be improved to achieve linked data between medical devices and data management platforms, which could effectively promote the practical deployment of AI systems.

From the human resource perspective, a training system for individuals specializing in medical informatization should be established. The awareness and capability of medical workers toward AI should be improved, and their traditional workflow and mindset should change [18]. At the same time, medical workers should be effectively encouraged to engage in research combining AI with medical diagnosis and treatment. AI could be used as a new method to promote the development of medical theories. Finally, AI could also be applied in medical education to shorten the training cycle of high-level medical personnel.

4.3 Producing and improving relevant matched policies

For the practical use of intelligent diagnosis and treatment systems, relevant regulations and standards in product development, manufacturing, and registration are necessary. Compared to developed countries, China has not yet established primary standards for the medical information industry or the applicable regulations and policies for intelligent systems. It is recommended that the government expedite the establishment of industry standards for medical information and the AI industry to address technological advancements for systems and devices with suitable policy- and regulation-level support in the market.

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