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Artificial intelligence meets traditional Chinese medicine: a bridge to opening the magic box of sphygmopalpation for pulse pattern recognition

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A B S T R A C T

Artificial intelligence (AI) aims to mimic human cognitive functions and execute intellectual activities like that performed by humans dealing with an uncertain environment. The rapid development of AI technology provides powerful tools to analyze massive amounts of data, facilitating physicians to make better clinical decisions or even replace human judgment in healthcare. Advanced AI technology also creates novel opportunities for exploring the scientific basis of traditional Chinese medicine (TCM) and developing the standardization and digitization of TCM pulse diagnostic methodology. In the present study, we review and discuss the potential application of AI technology in TCM pulse diagnosis. The major contents include the following aspects: (1) a brief introduction of the general concepts and knowledge of TCM pulse diagnosis or palpation, (2) landmark developments in AI technology and the applications of common AI deep learning algorithms in medical practice, (3) the current progress of AI technology in TCM pulse diagnosis, (4) challenges and perspectives of AI technology in TCM pulse diagnosis. In conclusion, the pairing of TCM with modern AI technology will bring novel insights into understanding the scientific principles underlying TCM pulse diagnosis and creating opportunities for the development of AI deep learning technology for the standardization and digitalization of TCM pulse diagnosis.

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1 Overview of pulse diagnosis or palpation in traditional Chinese medicine (TCM)

TCM is a unique medical system that has developed in China over thousands of years. The origins of TCM can be dated back from the Neolithic period (新石器时代) to the Spring and Autumn periods (770–476 BCE). The legends of *Fu Xi* (伏曦) making nine needles and *Shen Nong* (神农) tasting hundreds of medicinal herbs are generally recognized as the beginning of TCM. TCM physicians use four diagnostic methods comprising inspection (望), auscultation and olfaction (闻), inquiry (问), and palpation (切) to collect clinical information and make diagnoses in TCM constitution and syndrome pattern recognition. Palpation or TCM sphygmopalpation, a combination of human arterial pulse-sensing and diagnosis, has been used by TCM physicians since the Han Dynasty (202 BCE – 220 CE). In addition to western medicine practitioners, who only use palpation for estimating cardiovascular function based on pulse rate and rhythm, TCM practitioners generally use their finger-based perception and their own experience to draw conclusions about patients' holistic health status.

According to the classical TCM concept recorded in an ancient Chinese masterpiece called *The Pulse Classic* (*Mai Jing*, 《脉经》) and the theory of TCM, pulse signs, named *Mai Xiang* (脉象), at different locations of the wrist, named *Cun* (寸), *Guan* (关), and *Chi* (尺), could reflect the health conditions of the internal organs, named *Zang-fu* (脏腑). The *Mai Xiang* is an important external sign of the *Zang-xiang* (脏象) reflecting the status of *Zang-fu* in regulating the formation, distribution, and movement of Qi-blood and the Yin-Yang balances. A TCM practitioner generally inspects the *Mai Xiang* at the *Cun* (寸), *Guan* (关), and *Chi* (尺) wrist positions with different finger pressures referred to as *Ju* (superficial finger pressure, 举), *An* (middle finger pressure, 按), and *Xun* (deep seeking pulse with high finger pressure, 寻). In a quiet environment, the TCM practitioner would simply use finger inspection to determine wrist pulse variables, including the rate, depth, rhythm, width, smoothness, force, stiffness, strength, and surrounding area for pulse diagnosis, and then integrate the *Mai Xiang* with other disease signs and symptoms for disease diagnosis and syndrome differentiation. These pulse parameters are important external body signs reflecting the physiological and pathological status of the *Zang-fu* systems and the corresponding status of Qi-blood and Yin-Yang. According to classical TCM theory, the characteristics of the pulses at the left *Cun*, *Guan*, and *Chi* reflect the functional status of the heart, liver, and kidney Yin, respectively. Meanwhile, the characteristics of the pulses at the right *Cun*, *Guan*, and *Chi* indicate the functional status of the lung, spleen, and kidney Yang. If there is any change in the internal organs and the related functions, the pulse parameters will be affected, forming a unique diagnostic basis. Historically, *Yellow Emperor's Inner Classics* (*Huang Di Nei Jing*, 《黄帝内经》) documented 30 types of pulse patterns and *The Pulse Classic* (*Mai Jing*, 《脉经》) documented 24 types of pulse patterns. Nowadays, there are 28 commonly identified pulse patterns as detailed by Dr. LI Shizhen in his famous book, the *Bin Hu Mai Xue* (《濒湖脉学》) published during the *Ming* Dynasty, including floating, sunken, slow, rapid, surging, fine, vacuous, replete, long, short, slippery, rough, string-like, tight, soggy, moderate, faint, weak, dissipated, hollow, drumskin, firm, hidden, stirred, intermittent, bound, and skipping and racing [1]. In TCM practice, patients can present with many complex pulse conditions with simultaneously mixed pulse patterns. With the accumulation of clinical experience, senior TCM practitioners have developed advanced abilities to sense different pulse patterns, even with minor changes in pulse parameters, for their diagnostics. Although general descriptions of the pulse patterns are well documented, different TCM practitioners often yield different interpretations of the pulse patterns and make various pulse diagnoses that depend on their own experiences and understanding of the pulse patterns. In addition, the TCM pulse interpretation should be integrated with other clinical information obtained from other inspections to make an individualized diagnosis of TCM syndrome differentiation and personalized treatment. Thus, the standardization of TCM pulse diagnosis is important in the tradition and development of TCM.

However, the standardization and digitization of pulse diagnoses are challenging missions. The recognition of pulse characteristics is based on the subjective experiences and specific feelings of experienced TCM practitioners. It is worthwhile to study TCM pulse diagnosis by integrating classic TCM pulse recognitions and advanced scientific approaches. Hence, an ideal measurement system for mimicking TCM practitioners must have the ability to provide different levels of pressure, precisely measure arterial pulses at the *Cun, Guan*, and *Chi* points, and classify 28 types of arterial pulse according to TCM theory. For decades, large efforts have been made to explore the scientific basis and digitize the findings of TCM practitioners by integrating multidisciplinary approaches including biomedicine, mathematics, physics, bioengineering, and computer science. Different pulse diagnostic instruments have been developed to capture the arterial pulse at the human wrist [2-5]. These studies can be categorized into two types: the objectification of pulse measurements and the scientific explanation of the pulse mechanisms for the modernization of pulse diagnosis. These machines have often exhibited design issues that hinder their development. Some, for example, simply used a single pressure sensor for arterial pulse recording and diagnosis without considering the position where the pulse should be taken [6]. Other machines recorded pulses from different positions but still omitted the importance of the applied pressure [7-9]. However, in TCM practice, a conclusive pulse diagnosis can be achieved only by analyzing all pulses measured at three positions and their variations under different applied pressures. In addition to the development of instruments for pulse measurement, pulse pattern classification and analysis are also important aspects in standardizing TCM pulse diagnosis. However, traditional scientific approaches are poorly suited to deal with such big data and complex variables involved in the TCM pulse diagnosis. Excitingly, the rapid development and application of artificial intelligence (AI) in medical science provides new opportunities for exploring the scientific basis and digitalizing pulse variables in TCM pulse diagnosis.

2 Current progress of AI application in medical practice

Intelligence is defined as the capacity of a system to act appropriately in an uncertain environment [10, 11]. For artificial intelligence, there are strong AI and weak AI definitions. Strong AI is a system that can operated in the same way as human intelligence based on non-natural artificial hardware and software construction. A strong AI is also defined as an artificial general intelligence with the universal ability to cope with an uncertain environment and be able to replace a person in a required situation. Weak AI refers to a system in which the intelligence works to efficiently execute intellectual activities with a capacity like that of human performance [12, 13].

The concept of AI can be dated to the 1950s [14]. A neural analog reinforcement calculator was developed as the first neural network by Marvin Minsky and Dean Edmunds in 1951. The first AI program was developed by Allen Newell and Herbert Simon in 1955; the term of "machine learning" was then proposed by Arthur Samuel for weak AI in 1959. An AI program, ELIZA, which allowed people to communicate with machines in English, was introduced by Joseph Weizenbaum in 1965. A MYCIN expert system for diagnosing and treating infectious diseases was reported in 1972 (https://en.wikipedia.org/wiki/Mycin). The development of artificial neural networks (ANNs), data mining, machine deep learning, and cognitive science have created great opportunities for medical applications. For example, in 1980, a fuzzy logical model was introduced for computer-assisted medical diagnosis [15]. In 2009, a Bayesian network model was introduced for the diagnosis of psychiatric diseases. Particularly, the deep learning technology greatly extends the application of classic neural network techniques in medical practice. The rapid development of modern computer science enables deep learning to form neural networks that contain large amounts of layers, allowing deep learning to explore complex non-linear patterns in datasets. In a complex natural system, such as the human body, deep learning approaches can use complex and large hidden layers, and the algorithms can deal with complex data and various structures [16]. Convolutional neural networks (CNNs) are commonly used deep learning algorithms in medical practice. CNNs can handle high-dimensional data and large number of traits. The CNN was first proposed and advocated for high-dimensional imaging analysis by LECUN et al. [17] in 1998. The implementation of CNN includes powerful software packages such as Caffe from Berkley AI Research, CNTK from Microsoft, and TensorFlow from Google. CNNs have been successfully implemented to assist in disease diagnosis, such as cancer, stroke, and diabetes [18]. For instance, ESTEVA et al. [19] reported the superior performance of a CNN in identifying skin cancer from clinical images with over 90% accuracy for the correct prediction of both malignant and benign lesions. The CNN algorithm has a high sensitivity and specificity of over 90% for identifying diabetic retinopathy based on retinal fundus photography [20]. In addition to the CNNs, other deep learning algorithms, such as recurrent neural networks, deep belief networks, and deep neural networks, have also been used in medical diagnosis [21-23].

In recent years, the development of wearable health devices and powerful personal network analytic technologies have greatly facilitated the application of AI in monitoring different human diseases, such as cardiovascular diseases (CVD), diabetes, cancer, sleep disorders, mental illness, and dental disease [24-30]. For example, the combination of heart rate (HR) measurements, internet of things (IoT), and an advanced AI system forms a wireless Heart Health Monitoring Service Platform (HHMSP). The service platform facilitates a hybrid diagnosis process for monitoring the safety of atrial fibrillation and other cardiovascular disorders. The AI system improves the outcomes of patients where machines and medical practitioners work cooperatively [24]. A wearable health device can be used in hemodialysis patients by measuring their HR, arrhythmia, blood pressure, hyperkalemia, fluid overload, and physical activity, permitting 4P medicine (predictive, precise, preventive, and personalized) for disease dialysis and patient care [31]. Machine learning algorithms for large-scale data analysis could expand to quantitative applications of 12-lead electrocardiography in medical decision-making and provide clues regarding acute coronary syndrome and myocardial ischemic episodes [32-34]. In coronary angiography operations, AI machine learning can be used to monitor aortic pressure waveform analysis, facilitating the management of patient safety [35]. Therefore, AI technology has become one of the most important components of modern medicine, greatly facilitating medical practice and patient care. Meanwhile, the achievements and experiences of using AI technology in western medicine also provide important cues and methodologies to explore the scientific basis of TCM pulse diagnosis.

3 Current progress of application of AI technology in TCM pulse diagnosis

In TCM pulse diagnosis, the most common and effective technique is the use of ANNs, a machine learning method. Four important design parameters influence the performance of an ANN: data sourcing, the size of the training sets, input and output selection, and network structure. In 2005, ZHAO et al. [36] employed neural network models to monitor blood pressure propagation from the wrist to the fingertip. They reported that the fingertip had a similar pulse waveform to that at the wrist radial artery. In 2007, a fuzzy neural network was introduced to classify pulse images based on the knowledge of TCM experts in pulse diagnosis. The designed classifier had an accuracy of 91% in identifying 18 patterns of pulse images [37]. Given that a typical pulse signal is composed of periodic systolic and diastolic waves, a modified Gaussian model was adopted to fit the pulse signal, and the modeling parameters were taken as features. Subsequently, a fuzzy C-means classifier was applied for wrist pulse signal pattern classifications from 100 healthy persons and 88 patients. The results demonstrated the effectiveness of the proposed method for computerized wrist pulse diagnosis [38]. TANG et al. [39] used four-layer ANN models trained with 45 hidden neurons and the Levenberg-Marquardt algorithm in a TCM pulse study of 229 subjects. The output neurons were TCM pulse qualities operationalized as the intensity of the depth, rate, regularity, width, length, smoothness, stiffness, and strength at six locations (*Cun, Guan*, and *Chi* of both the left and right wrists). The input neurons were the physical variables of the arterial pressure waveform acquired from the six locations using a pulse acquisition device. The study suggests that the ANN model could be a powerful tool for TCM practitioners to collect pulse information in telemedicine [39]. They also validated the accuracy, specificity, and sensitivity of ANN in a normal control group with 139 subjects and a hypertension group with 121 cases. The ANN pulse diagnostic model had approximately 80% accuracy and 70% – 90% specificity and sensitivity [40]. An ANN was also used to quantitatively standardize pulse-taking depths based on the width of the artery with different finger pressures. The study revealed that the ANN model significantly enhanced the accuracy of detecting pulse signals at different depths, providing TCM practitioners with more reliable pulse information [41]. LUO et al. [42] used machine learning to classify and predict the changes in radial pulse waves in 479 healthy subjects and 450 patients with hypertension. A self-developed H20 Questionnaire and pulse wave information were utilized as input variables to obtain different machine learning models. The results obtained from traditional analysis and machine learning indicate that multiple parameters of the pulse wave, including cardiovascular function parameter h1/t1, gravity wave amplitude h5, duration of the beginning of tidal wave t2, and diastolic area, were correlated with hypertension [42]. Recently, CHEN et al. [43] conducted a case-control study to test various machine learning models, such as linear discriminant analysis, support vector machines, and random forests, and explored the feasibility of using pulse waves to diagnose and monitor type 2 diabetes. The support vector machine with polynomial kernel algorithms revealed a prediction accuracy of 96.35% for diabetes patients but had accuracy < 70% when the diabetes patients also had hypertension and hyperlipidemia [25]. In addition to TCM pulse diagnosis, deep learning technology has also been used to study the correlation between pulse pressure wave and pregnancy [43], computer-assisted TCM lip diagnosis [44], TCM syndrome prediction [45], Qigong exercises and medical intervention [46], and computer-aided TCM decision-making [47]. Thus, ANNs and deep learning technology exert their unique advantages providing profound perspectives in TCM diagnosis and treatment.

4 Challenges and perspectives of AI technology in TCM pulse diagnosis

Current progress in ANNs and deep learning technology indeed creates a great opportunity for crosstalk between ancient TCM pulse diagnosis theory and modern science, facilitating the standardization and digitalization of TCM pulse diagnosis. However, there are several bottlenecks for the development of AI technology for TCM pulse diagnosis. The first challenge is the correlation and consistency of the subjective finger sensations of a TCM practitioner to pulse patterns, and the objective machine-recorded pulse wave variables. Although the pulse TCM patterns are clearly described in TCM textbooks, different TCM practitioners often provide different interpretations of pulse diagnoses, which depend on their own experiences and understanding of pulse patterns. Even the same TCM practitioner may make different pulse diagnoses in response to similar pulse characteristics in the same patients under different circumstances. Consistency is a prerequisite for AI deep learning in the recognition of machine-recorded pulse waves. Second, the mismatches of time, pressures, and positions between the TCM practitioners and machine data collections would result in artifacts for ANN algorithms and deep learning. Third, the performance of these algorithms is generally restricted due to the limited amount and range of data obtained from a single patient. Additionally, most AI network systems are based on technologies from wearable health devices that were developed without strictly following the written rules of TCM pulse diagnosis. Although large efforts have been made to develop instruments and methodologies for pulse measurement, the instrumentation and analysis methodologies are seldom accepted by TCM practitioners in their clinical practice. One of the major arguments is that the interpretation of results obtained from the machine-recorded pulse waves could not represent their real recognition of the pulse patterns and related clinical significance. The following strategies and efforts might be potential routes to resolution. (1) Developing personalized TCM pulse diagnostic expert systems based on TCM principles and practice. To develop AI algorithms for TCM diagnosis, we should respect the basic principles and methodology of TCM, and machine learning should reflect the personal pulse recognitions of the individual experienced TCM practitioners. For the first step, developing individualized and personalized AI-assistant pulse diagnostic expert systems could be a good strategy that is generally acceptable for TCM practitioners. By using AI-assisted data analytic systems, we could recruit large numbers of patients and healthy subjects from their daily clinical consultations. We could establish a pulse diagnostic model for individual TCM practitioners with the capacity of real-time reporting of their recognition of common pulse patterns. With large sample sizes for the AI algorithm, we could filter the noise and potential interference and eventually develop AI-assisted individualized pulse diagnostic systems. In the second stage, we recruited different TCM practitioners matched with similar expertise and working experience and used AI systems to compare and analyze their consistency in the same patients with similar pulse variables as recorded by a machine. Under the inconsistent interpretations of the pulse patterns, these TCM practitioners could have group discussions to resolve potential differences in their interpretations of the definition of pulse patterns. Subsequently, the AI algorithm and ANNs will learn the consistent and inconsistent components of pulse recognition from different TCM practitioners. The crosstalk between TCM practitioners and AI machines would provide potential resolutions for the standardization and digitalization of TCM pulse diagnosis. (2) Developing real-time AI data collection and analytic systems. With the rapid progress of AI technology, AI algorithms for deep learning have attracted substantial attention in the study of TCM pulse diagnosis. However, their real-time implementation is still an obstacle. The use of real-world evidence would provide a potential resolution. We developed a remote data collection and transport system that simultaneously records the pulse information from the same positions as the fingers of the TCM practitioner. In addition, we could use AI technology to integrate databases including pulse diagnosis, body constitution, TCM syndrome differentiation information, and other healthcare information, providing AI-assisted integrative health management systems for healthcare and personalized medicine.

Recently, we developed a novel pulse-sensing platform (PSP) that can record and classify arterial human pulses using the TCM approach [48, 49] This platform can be divided into two major parts: (1) a palpation robotic hand (PRH), which consists of three robotic fingers for pulse measurement, and (2) a dedicated control and signal processing algorithm for pulse data filtering and classification. To fully mimic TCM practitioners' skills, the three robotic fingers in the PRH can be individually actuated and generate different levels of fingertip pressures. We conducted pilot studies using the developed PSP for pulse classification. We selected 11 healthy volunteers and measured their blood pressure and oxygen saturation using a sphygmomanometer and pulse oximeter, respectively. A senior TCM expert with over 30 years' experience made the pulse diagnosis, and the pulse patterns diagnosed were used as the target output to perform supervised learning. By using a PRH, we collected arterial pulse data. Notably, the consistent recognition of pulse data characteristics by TCM practitioners is essential for developing AI learning in TCM sphygmopalpation. To test the consistency of TCM practitioner's pulse diagnoses, we conducted two pilot studies with a one-year time gap in data collection. A double-blind method was used to test the consistency of pulse diagnoses by comparing the data distribution characteristics obtained using the PSP system. Our ANN was trained using the collected sample under a supervised learning algorithm. The confusion matrix shows the recognition results for six pulse types among the 11 subjects. Interestingly, the experienced senior TCM practitioners could distinguish very small changes in the frequency and flow movement of the pulse to identify different pulse patterns as collected by the PSP. The PSP platform classified pulse patterns with an overall success rate of 97.5%. We are working on an advanced AI system to recognize common pulse patterns diagnosed by experienced TCM practitioners. With further development and big data analysis, we believe that AI technology can provide a conclusive pulse diagnosis according to what it has learned. This AI system will benefit the development of more reliable and accessible TCM by providing quantifiable arterial pulse information. Importantly, AI technology will facilitate the scientific community to understand the scientific basis of the ancient diagnostic arts and transfer the knowledge and experiences of TCM practitioners and their fingers' sensations for the continuance and development of TCM.

In conclusion, AI is an attractive and powerful tool for advanced medical practice in today's digital medical age. The machine learning-based assistive systems enable the extraction and mining of abundant medical data for guiding disease diagnosis and treatment in western medicine. Current progress in AI assistive TCM pulse diagnosis has achieved high predictive accuracy and has shown great potential to open the magic box to understand the principles of TCM pulse diagnosis and facilitate the recognition of experienced TCM practitioners. Further work is desirable for the standardization and digitalization of TCM pulse diagnosis.

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Competing interests

The authors declare no conflict of interest.

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当人工智能遇上传统中医:通往识别脉象模式的宝盒

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【摘要】人工智能(AI)能够模仿人类的认知功能并具有执行类似于人类应对不确定环境下智力活动的能力。人工智能技术的迅速发展产生了能够分析大数据的强大工具,人工智能用于医疗服务可以为医生作出更准确的临床决策,甚至具有取代人类在医疗保健领域认知的潜能。先进的人工智能技术也为探索传统中医药的科学基础以及发展标准化和数字化中医脉象诊断方法创造了新的机遇。我们在本研究回顾并讨论了人工智能技术在中医脉诊中的潜在应用,主要讨论了以下方面内容:(1)简要介绍中医脉诊的基本概念和知识;(2)人工智能技术的标志性发展以及其深度学习程序在医学实践中的应用;(3)人工智能技术在中医脉诊中的最新进展;(4)人工智能技术在中医脉诊中的挑战和前景。总之,传统中医与现代人工智能技术结合将为理解中医脉诊基础的科学原理带来新的思路,并为人工智能深度学习技术的发展创造机会,以实现中医脉诊的标准化和数码化。

【关键词】人工智能;传统中医;触诊;脉冲模式识别;脉诊