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Data-driven based four examinations in TCM: a survey

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ABSTRACT

Traditional Chinese medicine (TCM) diagnosis is a unique disease diagnosis method with thousands of years of TCM theory and effective experience. Its thinking mode in the process is different from that of modern medicine, which includes the essence of TCM theory. From the perspective of clinical application, the four diagnostic methods of TCM, including inspection, auscultation and olfaction, inquiry, and palpation, have been widely accepted by TCM practitioners worldwide. With the rise of artificial intelligence (AI) over the past decades, AI based TCM diagnosis has also grown rapidly, marked by the emerging of a large number of data-driven deep learning models. In this paper, our aim is to simply but systematically review the development of the data-driven technologies applied to the four diagnostic approaches, i.e. the four examinations, in TCM, including data sets, digital signal acquisition devices, and learning based computational algorithms, to better analyze the development of AI-based TCM diagnosis, and provide references for new research and its applications in TCM settings in the future.

1 Introduction

Traditional Chinese medicine (TCM), rich in practical experience and theories, is a popular traditional medicine employed in many countries and regions around the world. With its specific holistic views on "body and spirit" "overall review", and "four diagnoses" as well as syndrome differentiation and treatment, the evaluation of TCM treatment has become increasingly characteristic and feasible [1]. Treatment based on syndrome differentiation is the core of TCM clinical examination, whose theoretical system has been tested and verified by TCM practices for thousands of years. During TCM examinations, the processes of inspection, auscultation and olfactory, inquiry, and palpitation exhibit the unique advantages of TCM theories and the effectiveness of its practice. The core theories, along with the diagnostic methods for syndrome differentiation treatment, have accumulated countless empirical data, offering an important resource for the research and development of TCM [2].

Although TCM diagnosis mainly relies on the holistic, dynamic, and individualized understanding of our bodies, these diagnostic methods are experience based, leaving tremendous potential for TCM to be exploited [1]. However, lacking technologies in this regard before has left the objectified exploitation of these TCM theories and methods unresolved for a long time. But as the modernization and internationalization of TCM grow, its value has been gradually recognized around the world. Modern intelligent technologies have been used to tackle the problems, such as making the techniques employed in TCM diagnosis and treatment process more standardized and

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digitalized [2].

Artificial intelligence (AI) as an important branch of computer science has already been well-developed after 60 years since its appearance, with evolving applications in many fields. Particularly, the successful application of AlphaGo under the guidance of deep learning theory has highlighted the advantages of artificial neural network (ANN) by integrating learning and training to achieve intelligence [2]. The advancement of AI technologies, which are now widely applied in the healthcare industry, has provided an opportunity for medical development. Big data is the cornerstone of AI technology and an important factor that determines whether AI technology can be effectively performed. Furthermore, data in a large scale play critical roles in clinical decisions. With data driven modules, not only the scientificity and validity of AI technologies can be ensured, but also, by a narrow definition, its human-like thinking and intelligence can be truly realized [3].

Data-driven based learning focuses on how to extract knowledge from large data sets, and applies them to solve problems in various tasks in different fields [4]. In the use of TCM diagnosis, the data-driven process is made up of the following steps: preparation of data about four examinations for analysis, formulation of data-driven based scientific problems, data analysis, acquirement of solutions, and then making high-quality decisions on numerous occasions. Many information technologies from computer science, statistical analysis, machine learning, data visualization, deep learning, and complex systems have been involved in this process [5].

The four diagnostic approaches in TCM, inspection, auscultation and olfactory, inquiry, and palpitation, have inherited the wisdom of ancient Chinese people and are still in use today [6]. The relationships among the four approaches are depicted in Figure 1. However, traditional four examinations often rely on physicians' subjectivity, such as their observations and feelings, and are greatly dependent on experience. Besides, external factors such as temperature and light can impose influence on the diagnostic results. To address these issues and obtain more convincing and reliable diagnostic results, natural language processing, computer vision, knowledge graphs, and deep learning technologies have been employed over the past few years to promote the accuracy and liability of the four TCM examinations. With the employment of these information technologies, new opportunities have been opened up for TCM development. Informatization, digitization, and standardization in TCM are all becoming possibilities.

Information technologies have not only addressed the issues in TCM such as subjectivity and insufficiency of objective data, but have also laid solid foundations for data analysis. With the support of modern TCM diagnostic technologies, the data produced by them, and the core philosophies in TCM syndrome differentiation, research on TCM intelligent diagnosis and treatment have been gradually carried out. To better investigate the progress of TCM diagnosis from the computation view, we have a short but systematic literature review presented in this paper for related researchers.

2 Inspection

Inspection in TCM aims to acquire information by observation. The condition of patients can be evaluated by observing parts of patients' bodies for changes. Contrary to western medicine, which is based on objective evidence, TCM mostly has subjective opinions of a medical practitioner as a diagnostic basis, and those very experienced TCM physicians could offer diagnostic results via inspection without even demonstrating the process and self-ratiocinating [7]. Figure 2 and 3 show the details of the inspection according to the penetrance of viscera in TCM, and list some locations and information in TCM diagnosis. Contrary to the objective description of a patient in western medicine, the subjective opinions of medical practitioners are what made up of TCM inspection. What's more, TCM masters could make a diagnosis with inspection only [8].

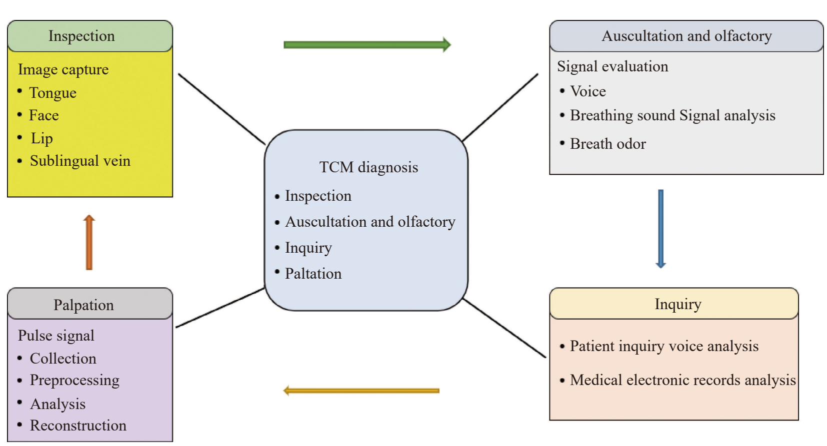

Figure 1 The schematics of the relationships of the four TCM diagnostic approaches: inspection, auscultation and olfactory, inquiry, and palpation

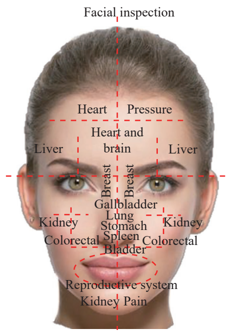

Figure 2 Face diagnosis partition

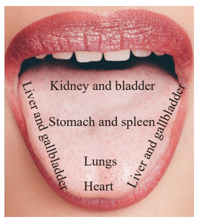

Figure 3 Chinese tongue diagnosis illustration

Over the past decades, research on AI-assisted inspection diagnosis has matured and perfected. The AI-assisted process can be roughly divided into several steps: image acquisition, image prepossessing, image segmentation, feature extraction/selection, and classification and recognition. Eye, tongue, and face diagnosis are the focus of studies on AI assisted inspection, which is based on computational images and AI technologies. Most of the inspections of body parts such as the eye, tongue, and face for diagnosis are achieved by observing the images of respective body parts [9].

Visual diagnosis falls under the local inspection category in TCM. The first record of visual diagnosis is in *Spiritual Pivot* (*Ling Shu*, 《灵枢》). "The essense of the five zang-organs and the six fu-organs all flow upwards into the eyes to enable the eyes to see [10]." TCM visual diagnosis is an approach through which physicians observe patients' eyes to identify the location and nature of lesions. Besides, disease progression and pathological mechanisms can be reflected by the state of the eyes. As the technologies of medical image analysis grow, TCM visual diagnosis has been able to seek assistance from AI technologies [11]. YANG's group analyzed the iris images of 350 patients unprecedentedly, and combined iris images with TCM theories to define the abnormalities in the iris, matching the abnormalities with possible diseases [12]. Following this innovation, many researchers carried out new studies on TCM visual diagnosis based on fundus image processing [13-17]. Machine learning based methods have been used repeatedly in this subject. NAVEED et al. [18] and KANSAL et al. [19] proposed several methods for visual diagnosis with machine learning, making great contributions to this field.

At the same time, studies on tongue and face diagnosis have become trending. Many Chinese scholars proposed a series of protocols for machine learning to assist in the diagnosis. Even many scholars outside China place their focus on algorithm research on tongue and face segmentation and classification [20-23]. As a result, a series of intelligent equipments have thus been born. David Zhang's group can classify physical signs through objectification and intelligent classification of face color, facial gloss, and lip color [24]. Meanwhile, an intelligent instrument for tongue diagnosis to confirm TCM syndromes according to the characteristics of tongue color, shape, and coating has already made to the stage [25-27].

3 Auscultation and olfactory

Auscultation and olfactory mainly involve sound diagnosis and olfactory diagnosis. Doctors obtain diagnostic information by means of voices, breath, coughing, sneezing, vomiting, sigh, gastrointestinal peristalsis, and other sounds coming from the patients. Meanwhile, doctors can decide patients' conditions from the smell of their body and excreta, such as perspiration, urine, and excrement [28-30]. Figure 4 exhibits the auscultation of sound diagnosis on heart and lung. Auscultation research is carried out through from the front four aspects of sound or odor signal collection, pre-processing, feature extraction, and pathological diagnosis. Several efficient intelligent auscultation and olfactory instruments have been developed for this purpose [31-33]. AI-assisted auscultation and olfactory diagnosis are still mainly in the stage of theoretical research [34-36]. Noise is critical in TCM acoustic diagnosis. Subjects are generally required to utter specified sentences or syllables in an environment of 30 decibels or below 45 decibels. An effective framework for sampling and extracting audio features with consistently low noise is important, which makes pathological diagnosis through modeling analysis possible [37, 38]. CHIU et al. [39] initially proposed a TCM diagnosis based qualitative analysis framework for auscultation. They utilized a voice acquisition device in their research, and evaluated several acoustic parameters, finally found that the wave from the patient was effective for identifying the symptom of a certain disease [39]. Similar works have also been

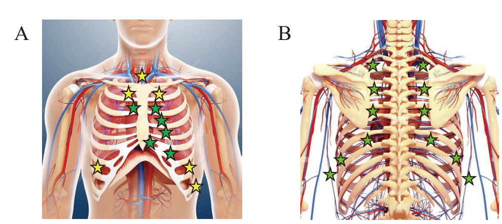

Figure 4 Auscultation on the heart and lung side

A, auscultation on the heart and lung from the front side. B, auscultation on the lung from the back side. The yellow and green stars represent lung and heart region, respectively.

proposed for evaluating the voice based TCM auscultation diagnosis [40, 41]. WU's group utilized a condenser microphone to collect a vowel for 2 s from 101 normal candidates and 34 subjects with Parkinson's syndrome, and simultaneously performed the Parkinson disease evaluation by analyzing the voice signal. The corresponding statistical results indicate that 96 kHz's sampling rate is suitable for detecting disease related signals [42].

Olfaction has also been investigated by researchers. Some research groups simulate a TCM practitioner's nose to capture patients' various situations to make a diagnosis [43]. The TCM theorem admitted that some diseases can cause special odors different from healthy people, which can be assent as a biomarker for disease classification tasks [43]. YU et al. [44] proposed a framework with a portable sensor array based gas evaluation system to collect patients' breath. After applying principal component analysis to reduce the high feature dimension, they finally found that the diabetic patients' breath has an acetone smell. The result indicates the possibility of developing diagnostic tools by using a gas sensor array in disease detection. GUO et al. [45] introduced a breath analysis system containing gas sampling bags to collect patients' breath, and expanded the types of disease detection by using odor evaluation. More recently, some studies selected three types of subjects: diabetic, healthy, and prediabetic subjects, and applied deep neural network architecture to extract effective features for making a diagnosis [46-48].

Compared to inspection, signals collected by auscultation and olfaction are trivia, because these signals are hard to capture and be evaluated for diagnosis. Thus, more learning based the developments of algorithms and instruments need to be designed for the research on auscultation and olfactory signals acquisition and evaluation in the future.

4 Inquiry

Inquiry diagnosis is the process of asking patients about their physiological feelings, in this way, the doctors can make some decision according to the information. In combination with information from facial color, tongue coating, odor and pulse variation indications, the doctor can draw conclusions about the physical condition of patients. Following the doctor's rules, AI-based TCM inquiry diagnosis aims at collecting and analyzing patients' information to inference their health status. AI based TCM diagnosis contains oral inquiry and questionnaires, and patients' medical records processing is also an important part of it. HONG et al. [49] proposed an inquiry diagnosis system containing medical records, inquiry, data visualization, and diagnostic modules, which was the whole process of TCM diagnosis to produce the final results. HU et al. [50] designed a similar system that could process patients' queries and characterize them into eleven classifications with the use of long short-term memory (LSTM) networks, listing itself as an auxiliary examination for patients' diagnosis. These results were effective in processing patients' questions. XU et al. [51] constructed a data set containing 1 127 cases with cardiovascular diseases and recorded four parts from text inquiry records, aiming at investigating diagnosis methods based on radial basis function (RBF) neural network. LIU et al. [52] evaluated the chronic gastritis syndrome in patients based on inquiry text records using deep learning framework. The results showed that the computation approach was effective in identifying syndromes, thus providing guidance for clinical diagnosis. Similar research was performed by MACIOCIA et al. [53] and MORO et al. [35], in which they proposed a diagnostic model to differentiate syndromes. WEN et al. [54] constructed a large dataset containing over 80 000 case records to train a model for named entity recognition, with its accuracy exceeding 70% in the results, suggesting the potential application of the dataset on clinical TCM inquiries. In the same way, ZHAO et al. [55] analyzed the correlation between inquiry information and TCM syndromes by using 3 707 case records of cardiovascular disease, and produced similar results to those of TCM experts', demonstrating that a model for TCM syndrome analysis can thus be constructed from the framework.

Medical records in computational inquiry are another factors contributing to TCM diagnosis. JIANG et al. [56] collected 436 candidates' medical records for diagnosing the sub-health status of patients with condition attributes. CHU et al. [57] used 664 medical records of 123 symptoms to extract features for syndrome differentiation, and a constructed multifunctional syndrome diagnosis framework. From a different perspective, ZHOU et al. [58] focused on the mining of symptoms and prescriptions by integrating the records of 40 000 TCM inpatients and outpatients to train a corporate data warehouse (CDW) model for performing syndrome differentiation. Some studies used speech, word block, and semantic features assisted by both shadow and deep learning for syndrome differentiation, with great progress attained in different diseases [59-62].

Computational inquiry in TCM diagnosis mainly focuses on text inquiry, questionnaires, and electronic records. Most of these works attempt to use eligible features from the data acquired for TCM diagnosis. It is necessary to develop novel AI models to process inquiry results in the future.

5 Palpitation

AI palpation is performed with the use of a belt-like pressure sensor and an amplifier binding to the wrist to determine pulse waveform via dynamic observation of the pulse, which imitates the pulse diagnosis of Chinese physicians. Figure 5 indicates the details of palpitation in TCM. To fulfill this purpose with assistance from AI, LUO et al. [63] proposed a diagnostic instrument that simulated palpitation based on TCM theories. This equipment could obtain signals at three positions with nine indicators [63-65]. Besides, BAE et al. [66] designed an arm holder connected to mobile phones to obtain pulse depth, with evaluations from 18 volunteers to prove its effectiveness. JIA et al. [67] reported a novel measurement for radial artery pulse waveform to evaluate the presence or absence of cardiovascular disease assisted with sensors. These sensors could obtain an optimal pulse waveform from fingers for clinical use. Inspired by these, a 3D system for pulse signal acquisition was born. This system is able to obtain both the width and amplitude of pulse waves in various situations. CHEN et al. [68] proposed a 3D pulse collecting system, a system with better performance than conventional approaches for pulse acquisition.

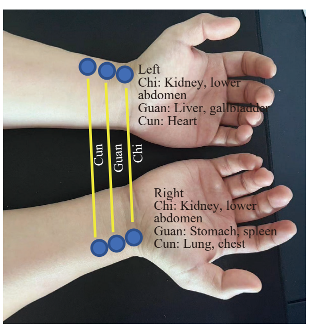

Figure 5 The diagram of principle for locating cun, guan, and chi

Apart from these instruments, various AI based wrist pulse diagnosis methods and systems have been proposed mainly for diabetes and cardiovascular disease diagnosis. HAO et al. [69] introduced an intelligent wristband acquisition terminal to collect the waveform of the pulse of four sub-types using data-driven based engineering pipelines. Moreover, ultrasound has been reported to bear the capacity to improve the liability of palpitation diagnosis, with results obtained explainable and diagnostic results more accurate than traditional approaches [70]. Some researchers have developed different models based on AI-assisted pulse waveform acquisition system for pulse analysis, most of which have used pulse transducer sensors to record the pulse wave, after which the waveform was processed with artificial neural networks to predict five types of pulse signals [71]. WANG et al. [72] introduced a novel model that integrated pulse pressure from multisensors and improved the accuracy with a photoelectric device. These experiments all demonstrated that the proposed diagnosis systems, models, and methods are applicable and useful for TCM treatment. The computational methods mentioned above showed the effectiveness of AI assisted pulse diagnosis on TCM disease diagnosis and in helping doctors understand patients' physical conditions better.

6 Data-driven approaches and big data in TCM

With the development of data science, data driven and its related methods have been widely applied in TCM diagnosis and treatment, enabling big data related techniques to become a well accepted subject in TCM studies. This integration between big data and TCM has become an emerging interdisciplinary field in Chinese academics. Currently, a large amount of personal data can be selected and stored in the Internet of Things network for acute disease treatment at a low cost. The impossible in ancient times becomes possible now. In the following part, we investigated the state-of-the-art big data in Table 1.

After deep learning takes its shape in machine learning field, using deep learning pipelines to extract simple features in a large amount of collected data seems to be easy access for TCM diagnosis. Deep learning, as a data driven pipeline, could yield ideal results in various clinical settings. However, data in large amount are often the key for a certain model to be trained through deep learning to let the model achieve good performance. This is an era of big data, AI based TCM diagnosis related to data-driven processes is a good opportunity for TCM development. The application of deep learning technology in processing big data of TCM is conducive to improving the accuracy of TCM diagnosis. However, there are still lots of things to be explored and done in the field of employing deep learning to AI based TCM diagnosis in the future.

7 Conclusion

In this paper, we reviewed some latest works in AI based TCM diagnosis. Particularly, we introduced four TCM diagnostic methods including inspection, auscultation and olfaction, inquiry, and palpation and the instruments applied to better carry out these methods. In these parts, we also introduced some devices and systems to acquire and process body signals along with corresponding learning based feature extraction methods/models. In addition, the pros and cons of the devices, models, and methods were discussed with the hope that improvement can be made on them to be used on more occasions, and provide guidance for future studies.

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Competing interests

The authors declare no conflict of interest.

Table 1 Summary of recently data set and methods

Diagnostic type	Collected dataset	Year	Author
Diabetes	Images	2017	ZHANG et al. [73]
10 diseases	Images	2020	WU et al. [74]
Liver disease	Images: hepatits, cirrhotic, liver cancer, and healthy	2019	HU et al. [59]
Lung and breast cancers	Images: healthy, lung cancer, and breast cancer	2017	CHEN et al. [75]
Body constitution	Images: face	2017	HUAN et al. [76]
Diabetes	Images	2017	SHU et al. [77]
Diabetes	Images	2018	SHU et al. [78]
Lip classification	Images: lips	2017	ZHOU et al. [79]
Diabetes and lung cancer	Images: healthy, diabetes, and lung cancer	2020	ZHOU et al. [80]
Diabetes and chronic kidney disease	Signal: healthy, diabetes, and chronic kidney	2021	ZHANG et al. [81]
Parkinson's disease	Signal: Parkinson's disease	2018	WU et al. [42]
Prediabetes and diabetes	Signal: healthy, prediabetes, and diabetic	2020	SARNO et al. [48]
Department classification	Text: labeled patients' questions	2018	HU et al. [50]
Syndrome differentiation of Yin deficiency and Yang deficiency	Text: TCM medical records	2019	HU et al. [82]
Lung cancer syndrome	Text: clinical records	2020	LIU et al. [60]
Rheumatoid arthritis syndrome	Text: records with syndrome labels	2020	XIE et al. [61]
Type 2 Diabetes	Text: diabetic patients	2019	HAO et al. [69]
Diabetes, nephritis, and cardiopathy	Signal: wrist pulse samples	2018	ZHANG et al. [83]
Diabetes, nephropathy, and hyperlipidemia	Signal: wrist pulse samples	2020	ZHANG et al. [84]
Diabetes and nephropathy	Signal: Healthy, diabetes, and nephropathy	2019	JIANG et al. [85]
Wiry pulse	Signal	2020	LAN et al. [86]
Nine body constitution types	Signal: 3 660 instances	2020	DAI et al. [87]
Breast tumor, heart disease, fatty liver, and lung tumor	Signal	2021	ZHOU et al. [88]
Coronary heart disease syndrome	141 subjects	2020	REN et al. [89]
TCM constitution	Multi-modal: tongue images, sound, and waveforms	2019	HUANG et al. [90]
Health condition	10 participants	2019	DING et al. [91]
Syndrome differentiation	Two datasets with 1 000 samples	2019	ZHANG et al. [92]

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基于数据驱动的中医四诊综述

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【摘要】中医诊断是基于中医学几千年的理论与有效经验而发展成的独特的疾病诊断方法，其过程中的思维模式区别于现代医学，囊括了中医理论的精髓。从临床应用的角度来说，中医望、闻、问、切四诊法目前已经在世界范围内从事中医相关工作者中得到了广泛认可。随着人工智能技术的快速发展，为实现中医四诊客观化，基于计算机辅助的中医诊断方法逐渐被人们所关注。尤其在深度学习模型大量应用的时代，以数据驱动为核心工作模式的工程范式，逐渐取代了人工操作，而成为工业界乃至学术界主要的研究方向。本文主要针对基于数据驱动模式的计算机辅助中医四诊方法开展调研，包括数据集、信号处理方法、深度学习算法等方面的内容，为相关研究人员提供一个综合的视角，并对未来可能的发展方向进行了简要论述。

【关键词】中医理论；中医四诊；数据驱动；机器学习；深度学习