Advances in AI-Driven Diagnostics for Traditional Chinese Medicine: A Review of Tongue, Face, and Pulse Analysis

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***Abstract*— This paper provides a systematic review of how artificial intelligence (AI) techniques have been applied in the diagnosis of traditional Chinese medicine (TCM). It highlights future directions for integrating the three key diagnostic indicators, tongue morphology, facial complexion, and pulse waveforms, into a unified framework. We found that existing studies rarely address the fundamental tension between TCM's dialectical reasoning and the data-driven optimization strategies typical of computer vision models. Beyond reviewing current computer vision applications in tongue, facial, and pulse diagnosis, this paper also highlights the deeper epistemological divide between TCM and AI methodologies.**

I. Introduction

For thousands of years, Traditional Chinese Medicine (TCM) has used three main ways to check a person's health. These are looking at the tongue, checking the color of the face, and feeling the pulse at the wrist. These methods came from old Chinese ideas about the body and health, and have been passed down through generations.

However, TCM faces some challenges in today's world. First, these key ideas like the balance of *Yin and Yang* and the flow of *Qi* are still hard to explain using modern medical science [1]. Second, different TCM doctors may give different diagnoses, since some methods rely on personal experience and the signs each person interprets. There is no fixed rule everyone follows. Also, it takes many years to practice professional TCM doctors, making it hard for new learners. Because of this, fewer young people are choosing to study TCM seriously in recent years.

In response to these problems in TCM diagnosis, researchers started looking into artificial intelligence (AI), and first AI diagnosing method came out as early as the 1970s [2], because AI is good at analyzing images and finding patterns, it offers a way to make some parts of diagnosis automatic. This can reduce the need for long-term training and help avoid differences caused by personal judgment.

Recent progress in computer vision has helped bring AI into TCM diagnosis. These new tools make diagnoses more accurate and less subjective than traditional manual methods. For example, the Two-Phase Deep Color Correction Network (TDCCN) helps standardize tongue images, so that signs of disease can be found more reliably [3]. AI-FR models can measure changes in facial color that are linked to certain illnesses [4]. The graph-based multichannel feature fusion (GBMFF) method improves how pulse signals are understood by using advanced ways to read waveforms [5]. Together, these methods help modernize TCM by making diagnoses more consistent to repeat.

Despite these technological advances, significant challenges remain in developing computer vision (CV) models capable of achieving diagnostic performance comparable to that of experienced TCM practitioners [6]. One of the most critical barriers is data acquisition: standardized signal and image collection devices are not widely available in clinical practice, resulting in limited and inconsistent training datasets for wrist pulse analysis. Facial image datasets also suffer from heterogeneous capture conditions across institutions and frequent gaps in corresponding clinical metadata, which collectively undermine data quality and model generalization.

A deeper problem comes from a basic mismatch between how TCM works and how CV models are trained. TCM uses dialectical thinking. It focuses on each person's unique condition. In contrast, CV models are built to find general patterns in data. This difference makes it hard to turn TCM's way of thinking into algorithms. As a result, many models focus on classifying symptoms, but they do not fully understand the idea of syndromes. They often focus on improving model accuracy and ignore the deeper gap in how knowledge is used.

This review uniquely proposes a multimodal framework that bridges the diagnostic paradigms of TCM with the machine learning typologies. It highlights two key issues. One is the importance of the multimodal method used in practical diagnosis of TCM, and the other is the importance of integrating the understanding of TCM syndromes with the data-driven AI approach. It also suggests that experts from different fields should work together more. This can help combine data-driven methods with the way TCM understands illness.

The review has three main goals. First, it aims to describe how computer vision is currently used in TCM diagnosis, with a focus on tongue, facial, and pulse analysis. Second, it seeks to outline the main technical challenges, including limited datasets, difficulties in model interpretability, and the lack of clinical validation. Third, it explores how deep learning models might be better aligned with the principles

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of syndrome differentiation in TCM.

II. Related work

Several review oriented studies have examined the intersection of artificial intelligence and TCM. Feng et al.[1] provided a general overview of AI applications in TCM treatment, while Guo et al.[6] discussed broader integration trends without focusing on diagnostic methods. Chen et al.[7] and Jia et al.[8] reviewed recent advances in tongue diagnosis, though their discussions primarily concentrated on image-based models. However, most existing reviews address only individual diagnostic components and rarely consider the alignment between computational models and TCM's interpretive logic. This paper differs by offering a unified review of tongue, facial, and pulse diagnostic methods. It also highlights the conceptual gap between data-driven approaches and the principles of syndrome differentiation in TCM.

Figure1 visualizes the citation relationships among core publications in this area, as generated using Connected Papers [9].

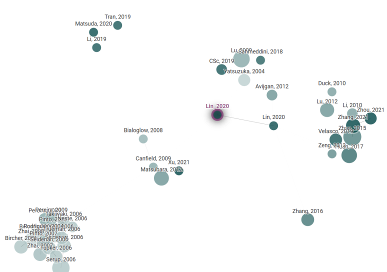

Fig. 1: The Related Paper of Computer Vision in TCM

III. Review Method

To ensure broad and balanced coverage of the topic, we adopted a systematic search strategy to collect relevant studies on AI applications in TCM. The search focused on three main areas: AI methods for tongue, facial, and pulse diagnosis; multimodal diagnostic approaches; and commonly used datasets in visual-based TCM research. We conducted a systematic search,using keywords "AI" AND "TCM" AND ("Tongue" OR "Facial" OR "Pulse") across popular academic databases, Google Scholar, IEEE Xplore and ScienceDirect. The search targeted titles, abstracts, and keywords, covering the years from 2005 to 2025. In total, this process yielded 33 publications that were initially identified as relevant.

After checking for relevance, some of the studies were removed. Firstly, though some studies, such as the TCM-ID database of Xue et al. [10], are related to TCM, they are more related to Chinese Herbal Medicine, but not the diagnosing method. Secondly, most traditional machine learning studies are related to evaluating the efficacy of herbal medicine and prescribing formulas to patients. For example, Wen et al. trained traditional machine learning models using the database of TCM formulas[11]. These studies do not have a strong relationship with TCM diagnosis. In the end, 26 studies were kept and analyzed in this review.

IV. Categorization Method

After review and categorization, the individual studies were grouped into diagnostic categories based on the type of data used (e.g., facial, tongue, or pulse data). So far, there has been very limited research about multimodal diagnostic categories combining more than one data source.

To give a clear overview of the selected studies, we grouped them based on their main research focus. As shown in Table I, each study was reviewed across five key areas: general AI use in TCM, and computer vision methods used for tongue, facial, and pulse diagnosis. We also noted whether the study used public TCM-related datasets. This way of grouping the studies helps guide the structure of the following sections. It also shows which types of diagnosis have received more attention in past research.

V. Computer Vision for Tongue Diagnosis

In TCM, the tongue is viewed as an important window into the body's internal state. It is believed to reflect internal organs *(Zang-Fu)* health, *Qi and blood* movement, and body fluids [7] balance. These ideas come from centuries of clinical observation. Over time, TCM practitioners have built connections between changes in the tongue—such as its shape, color, coating, and specific regions—and different physical conditions.

However, tongue diagnosis is not always reliable. It depends heavily on the doctor's experience [12], as well as their ability to observe details. Traditional tongue inspection lacks standard tools or clear rules. This makes the results hard to repeat in clinical settings. However,with the help of artificial intelligence and computer vision, tongue diagnosis may become more accurate, more objective, and easier to learn.

A. Tongue Image Color Correction

A color correction system can process original tongue images, allowing AI to diagnose diseases in a manner reminiscent of that of human TCM practitioners. In 2005, Zhang et al. introduced a computer-aided tongue diagnosis system (CATDS) [13]. It created a digital framework for tongue diagnosis. The team built a high-quality tongue image database and developed a color correction algorithm, using a new ColorChecker and Support Vector Regression (SVR). This method corrected an image distortions, which made images from different devices to be interchangeable, and achieved over 75% diagnosis accuracy in six disease groups. Even though early machine learning limitations, CATDS established essential workflows for tongue image preprocessing and underscored the need for device-agnostic standardization in digital TCM diagnostics.

In 2020, Xiaoguang Li et al. developed the TDCCN, enhancing tongue color classification [3]. The first phase, Objective Color Correction (OCC), reduced inter-device

TABLE I: Categorization of the Review

	AI Application in TCM	CV Applied in Tongue Diagnosis	CV Applied in Face Diagnosis	CV Applied in Pulse Diagnosis	Utilized Databases
Feng et al., 2021[1]	*				
Bai et al., 2011[2]	*				
Lu et al., 2020[3]	*	*			*
Wu et al., 2024[4]	*		*		*
Zhang et al., 2021[5]	*			*	*
Guo et al., 2019[6]	*				
Chen et al., 2021[7]	*	*			
Jia et al., 2024[8]	*	*			*
Liu et al., 2007[12]	*	*			
Zhang et al., 2006[13]	*	*			
Wang et al., 2020[14]	*	*			*
Chang et al., 2024[15]	*	*			
Li et al., 2020[16]	*	*			
Li et al., 2009[17]	*		*		*
Liu et al., 2017[18]	*		*		
Lin et al., 2020[19]	*		*		
Ning et al., 2020[20]	*		*		
Liu et al., 2018[21]	*		*		
Leung et al., 2021[22]	*			*	
Zhao et al., 2005[23]	*			*	
Tang et al., 2012[24]	*			*	
Chen et al., 2022[25]	*			*	*

Note: * indicates the category to which the reference belongs.

variability through a three-layer architecture. The second phase, Perceptual Color Correction (PCC), adapted outputs to environmental variables and clinician preferences using adjustable parameters. TDCCN demonstrated superior stability, achieving 15–22% lower mean color difference compared to conventional methods. However, its reliance on manual calibration suggests future potential for self-supervised color standardization.

B. *Techniques for Tongue Feature Extraction*

Tongue feature extraction is an important part of TCM diagnostics. In recent years, this process has improved with the help of AI. In 2020, Wang et al. explored how deep convolutional neural networks (CNNs) could be used to detect tooth marks on unhealthy tongues [14]. A deep learning model was trained to achieve a high accuracy to identify these features. CNNs made it possible to capture fine details and slight shape changes in the tongue. Many of these patterns are difficult to notice with the human eye, especially in routine clinical settings. In 2024, Chang et al. expanded on this work by building a large tongue image dataset and developing a faster detection model [15]. They collected many tongue images and worked with experienced TCM practitioners to label key features. With the YOLOv4-tiny model, they built a system that could detect these features. As a result, the model showed solid average precision (AP) scores across the four features: 47.67%, 58.94%, 71.25%, and 59.78%. These findings suggest that AI can help improve the speed and accuracy of tongue diagnosis.

Together, these studies show how AI can make tongue inspection tools more standardized and reliable. For TCM practitioners, this means they can spend less time on manual observation while improving the accuracy of their diagnoses.

C. *AI Training for Tongue Diagnosis*

Building on feature extraction, the next important step is to train models that can improve the accuracy and reliability of tongue image analysis in TCM. In 2020, Wang et al. used the ResNet34 architecture. [14]. This model was designed to solve a common problem with deep CNNs, where adding more layers can increase training errors. By using ResNet34, they reduced this issue and improved the model's generalization ability. This made the system more accurate and more reliable when applied to TCM diagnostics.

Around the same time, researchers began exploring the use of the YOLO algorithm for tongue image detection. In 2020, Li et al. applied YOLOv3 with pretrained COCO weights to tongue image tasks [16]. Their results showed that the model worked well, offering fast processing and high accuracy, with an impressive accuracy rate of 0.9262. Later, in 2024, Chang et al. introduced the YOLOv4-tiny model [15]. This model was able to detect features on the tongue with a level of precision close to that of human experts. These improvements point toward a future where AI tools can help practitioners make faster and more accurate decisions.

VI. Computer Vision for Facial Diagnosis

Facial diagnosis (*Wang* in TCM) is a key diagnostic method, which involves observing the color of a patient's face. It is believed to reflect the condition of the five zang organs through facial color [17]. Traditionally, TCM doctors rely on their own eyes to judge facial color, which often depends on the doctor's personal experience, and can be affected by light, temperature, and other external conditions. The factors may lead to different results between practitioners. Also, because there is no clear standard for measuring facial color, this method is hard to evaluate or improve with modern tools.

Today, new technology offers ways to improve facial diagnosis. Researchers are using multiple tools to build a facial diagnosis system. In this way, facial analysis in TCM can become more reliable and consistent, while still keeping its traditional ideas.

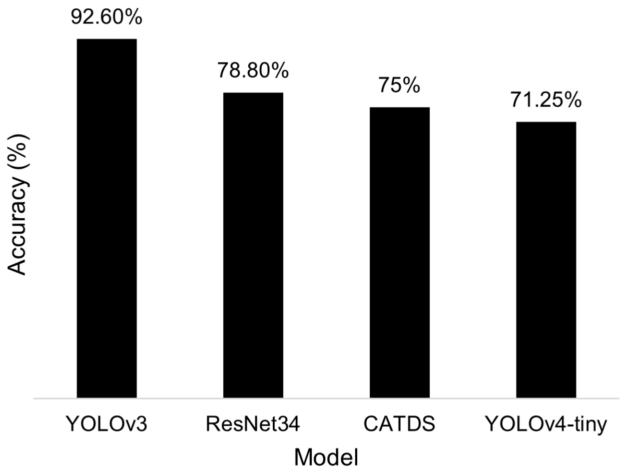

Fig. 2: Performance comparison of AI models for tongue diagnosis

A. *Classification of Facial Images for Diagnosis*

In TCM theory, analyzing facial color is an important part of diagnosis. In 2009, Li et al. carried out an important study to divide face into different regions and correcting color distortion of the image [17]. The researchers built a facial image database and used standard LED lighting and camera to keep stable of colors. Then, they used a linear unsupervised correction model to fix color errors. By comparing 24 standard color samples with the colors in the images, they found a correction values, which made the results more accurate.

Based on this earlier work, Liu et al. proposed an automatic method to segment the face. Their model used grayscale adaptive enhancement along with clustering techniques to improve image clarity and region separation [18]. Lin et al. took a different approach. They used color-space theory with machine learning tools like SVM and BP neural networks. Their method reached a recognition accuracy of 91.03% [19].

Some researchers keeps their eyes on the angle-related problems. Ning and Chen improved the image alignment problem by using SIFT feature matching and the RANSAC algorithm [20]. With the deep learning developing, Huang et al. used residual networks, and Jin et al. used CNNs to improve facial expression recognition method. Their models can distinguish faces even though the lighting was poor or part of the face was blocked.

There were also some advances in gender classification. For example, while Fekri-Ershad used a method which is based on iLBP. Zhang et al. used another method, which is called multi-scale fusion features [26]. However, further work is still needed. The facial recognition of deep learning is still based on data training, rather than based on the nature of identification.

VII. Computer Vision for Pulse Diagnosis

The wrist pulse is also an important sign in TCM. Pulse diagnosis, which is also called ”Qie” in Chinese, is one of the four TCM diagnosis methods. By feeling the pulse, an experienced TCM doctor can learn a lot about the condition of the blood vessels and internal organs without patients’ injury. In TCM theory, different wrist positions reflect various organs. Doctors observe pulse features like rate, depth, rhythm, width, smoothness, force, stiffness, and strength [22] to diagnose the condition of patients. However, many of these features can appear at the same time. This makes diagnosis more complex. Skilled TCM doctors rely on years of experience to detect patterns feature and judge the illness. This shows that traditional pulse diagnosis in TCM can be both careful and correct.

Right now, the limits of human-based pulse diagnosis are becoming more obvious. It depends heavily on many years of training and personal judgment, which can lead to different results between practitioners. Because of this, there’s a growing need for a more objective and efficient method. AI-based tools could help improve both the accuracy and consistency of wrist pulse diagnosis, making it a useful addition to traditional TCM practice.

A. *Current Progress of AI Applications in Pulse Diagnosis*

Artificial Neural Networks (ANNs) have been widely used in TCM pulse diagnosis because of their strength in pulse pattern recognition. In 2007, researchers used TCM knowledge to build a fuzzy neural network for classify the pulse pattern images. By using this method, the accuracy reached to 91% in identifying 18 different pulse types [23]. Later studies explored more ways to improve how pulse signals are processed. One approach used Gaussian models to break down pulse signals into systolic and diastolic parts. After that, these features were then analyzed using C-means classifiers. The results showed the reliable performance in a group of 100 healthy people and 88 patients. In 2012, Tang et al. built a four-layer ANN model, and trained it with the Levenberg–Marquardt algorithm [24]. This model was tested on data from 229 individuals and achieved an 80% accuracy rate. It also showed 70–90% sensitivity and specificity, which further confirmed the value of ANNs in clinical settings.

More recently, Chen et al. conducted a case–control study in 2020 , which compared several classification methods [25]. Their findings showed that the SVM method with polynomial kernels could distinguish type 2 diabetes from pulse wave signals with an accuracy of 96.35%. However, they also found that results became less stable when the method applied to more complex or multi-disease cases.

In recent years, deep learning methods have played a bigger role in improving the accuracy of TCM pulse diagnosis. In 2021, Zhang et al. proposed a new method that used Stacked Sparse Autoencoders (SSA) and wavelet scattering transforms to get the pulse features of raw pulse pattern data [5]. They also mentioned a method called GBMMF, which can work together with the k-Nearest Node Neighbors (k-NNN) algorithm.

After that, they used a Graph Convolutional Network (GCN) to classify the pulse data. This model showed a better performance than many traditional methods in pulse pattern classification, such as SVM, k-NN, LDA, Random Forest, CNN, and LSTM. It also showed higher accuracy and precision in multiple tests.

However, the limitation of these methods is also obvious. These methods are just machine learning and deep learning models of data training, but not for diagnosis based on TCM. As a result, these pulse diagnosis methods only suit TCM diagnosis assistance at the present stage.

VIII. Discussion

Table II provides an overview of the computer vision pipelines used in tongue, facial, and pulse diagnosis in TCM, highlighting common structures and key differences.

TABLE II: Comparative AI pipelines for tongue, facial, and pulse diagnosis in TCM

Step	Tongue	Facial	Pulse
Data Acquisition	Smartphone / TDS	Frontal image	Wrist sensors
Preprocessing	TDCCN, color fix	Region split, color correction	Waveform filtering
Feature Extraction	Teeth marks (YOLO)	Complexion color (SVM)	Wavelet + SSA
Model Training	ResNet34, YOLOv4	BPNN, CNN	GCN, ANN
Output	Diabetes	Gender	Pulse type
Accuracy	85–90% (YOLOv3)	91% (BPNN)	96%+ (SVM)

Under the theoretical framework of TCM, disease diagnosis involves multiple aspects, many of which are related to complex information such as image-based features.Traditional machine learning classifiers are hard to deal with such complex information, making the application of deep learning in TCM diagnosis necessary. However, since current datasets still require manual collection and labeling, it remains difficult to train models on large-scale data. Therefore, the advantages of traditional classifiers are still necessary to be considered.

A. Research Achievements

The recent developments in computer vision and AI have already improved the TCM diagnosis methods in image capture, color correction and feature recognition. These methods increased the objectivity, consistency and standardization compared to traditional TCM diagnosis.

Li et al. developed TDCCN to reduce color differences between devices [3]. This system reduced color variation by 15–22% between different devices by combining Objective Color Correction and Perceptual Color Correction modules. In addition, the YOLOv4-tiny model, achieved up to 40 FPS in detecting features like fissures and tooth marks. Its AP ranged from 47.67% to 71.25%, showing strong performance in real-time tasks [15]. Other models, like ResNet34, also showed a good performance. By using deep residual connections, the model achieved up to 78.77% accuracy in predicting diabetes from tongue images. The result proved the value of deep learning of tongue diagnosis in finding disease patterns.

In facial diagnosis field, researchers have improved complexion analysis by combining facial region division, color calibration, and feature extraction. Li et al. proposed a linear correction method, which uses a 24-color reference chart [17]. This made it possible to measure the five core facial colors in a uniform standardized way. Later studies used improved Local Binary Patterns (iLBP) and multi-scale fusion features (ms3f) to increase recognition accuracy. As a result, some models reached over 90% accuracy in some tasks like gender detection and facial color classification. By using AI facial diagnosis, the patient can rapidly get a basic diagnosis result , and the result can also be a reference of final diagnosis.

Pulse diagnosis is also shifting from traditional methods to deep learning. Early models, like fuzzy neural networks and SVMs, could classify pulse patterns with up to 91% accuracy [23]. Some recent papers use deep learning, like the mix of SSA, wavelet transforms, and GCN to analyze more complex pulse signals [5]. The model developed by Chen et al. , which used an SVM with a polynomial kernel even reached a 96.35% accuracy in recognizing type 2 diabetes from pulse waves [25]. These investigations on pulse pattern diagnosis can improve diagnostic efficiency and provide assistance for the TCM doctor.

In recent years, explainable AI (XAI) is also partly used in TCM diagnosis. Jing et al. applied SHAP method into a Chinese–Western medicine-integrated prediction model, which can diagnose diabetic peripheral neuropathy (DPN)[27]. This research marks a significant advance in integrating XAI with TCM diagnostic systems. Zhu et al. combined LIME and SHAP technology with the diagnosis of Ulcerative colitis (UC), building an explainable and highly accurate AI diagnosis model. However, the application of XAI is still at an early stage, which highlights the great potential for future integration of AI into TCM.

B. Limitations

Although research has made great progress recently, some critical issues still limit the widespread use of AI in TCM diagnosis.

The construction of TCM datasets is a major problem. Most of the AI based TCM diagnosis research relies on the datasets which are collected by research teams themselves or provided by TCM hospitals, and some of them are not public datasets because of privacy. This is exactly why the size and quality of datasets are usually uneven. Without a large amount of labeled data, training a high-speed and high-quality model is extremely difficult. In addition, some studies are based on datasets from western hospitals. However, the differences in classification and diagnosis between TCM and Western medicine may cause errors in dataset labeling.

Many AI models still don't perform well, either, especially in complex syndrome classification. Models like

ANNs and SVMs work well for predicting some single diseases. But their accuracy drops below 70% when faced with more complicated, multi-pattern cases. The limitation shows a gap between standard feature engineering and how TCM understands illness through dialectical thinking, and this gap cannot be reduced currently. For example, deep learning models can spot visible features. But they still can't fully catch the idea that the same disease may show up with different symptoms. This limits the ability of deep learning methods to explain various TCM symptoms.

What is more, these AI models are still really hard to use in real clinical settings. Most of the methods are tested in lab environments, but not in real hospitals or in TCM diagnosis practice. This makes it difficult to know if they actually work. Privacy is another key concern when capturing patients' images. In addition, the ways these models make decisions are often difficult to understand, so sometimes the model may arrive at the wrong diagnosis. This makes it harder for doctors to trust that the system can work alone, and it may need more trained TCM doctors to monitor its operation. XAI has become apparent as a potential solution by providing transparent explanations of the AI models' output [28].

IX. Conclusion

This review uniquely proposes a multimodal framework that bridges the diagnostic paradigms of TCM with AI typologies. The use of AI in TCM shows a way to connect traditional medical knowledge with modern methods, especially by CV. By focusing on tongue shape, facial color, and pulse waves, CV systems help reduce the subjectivity of TCM doctors, improve the consistency of diagnosis, and lower the need for years of training. Deep learning has shown desirable results. Some tongue and pulse analysis often reaches the performance of some trained doctors in specific tasks. These progresses can help to turn TCM's traditional ideas into more standard and testable tools. However, in most current systems, tongue, face, and pulse are still regarded as sole inputs, without combining them into a unified method.

How to match TCM's dialectical thinking with the statistical logic used in modern AI is also a significant challenge. Though there have been some TCM diagnosis models that applied to XAI method, which are still used for several TCM syndromes. At the same time, the XAI now used is essentially based on data, without understanding the core issue of diseases and the concept of multimodal diagnosis.

In the future, although improving the speed and accuracy of models is important for CV tasks in TCM, such as tongue, face, and pulse diagnosis, combining multiple diagnosis methods and applying explainable AI for TCM is also essential. These directions are key to bridging the gap between AI-based diagnosis and that of actual TCM doctors.

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