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Research Progress on Artificial Intelligence-Empowered Digitization of Tongue Diagnosis in Traditional Chinese Medicine

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Abstract

Tongue diagnosis, as the core content of inspection in Traditional Chinese Medicine (TCM), is a specific embodiment of the TCM diagnostic thinking of "observing the exterior to infer the interior" and has an irreplaceable value in TCM syndrome differentiation and treatment. However, traditional tongue diagnosis has inherent bottlenecks such as strong subjectivity, difficulty in quantification, and low inheritance efficiency, which restrict the modernization of TCM. With the breakthrough progress of artificial intelligence (AI) technology in fields such as computer vision, deep learning, and multimodal fusion, it has provided core technical support for solving the problems of "subjectivity and fuzziness" in tongue diagnosis and realizing the digitalization, objectivity, and intelligence of tongue image diagnosis. This paper systematically reviews the research progress of AI empowering the digitalization of tongue diagnosis, focuses on elaborating the evolution of core technologies such as tongue image preprocessing, intelligent feature recognition, and multimodal fusion, summarizes its clinical application practices in core scenarios including disease auxiliary diagnosis, health status identification, and dynamic efficacy monitoring, and deeply analyzes the current bottlenecks such as insufficient data standardization, lack of model interpretability, superficial integration of TCM theory and AI technology, and limited clinical promotion. In-depth analysis of these current situations and challenges is of great value for promoting the continuous deepening and application of AI in the digital diagnosis of TCM tongue image, and helps to facilitate the inheritance, innovation and modernization of TCM.

Keywords

Artificial Intelligence; Tongue Diagnosis; Digitalization; Current Situation.

1. Introduction

With the deep integration of informatization, intellectualization, and digitalization, humanity has officially entered the era of big data and artificial intelligence (AI). The rapid development and widespread application of AI technologies have injected strong momentum into the digital transformation of traditional Chinese medicine (TCM), particularly bringing unprecedented opportunities for the intelligent development of TCM tongue diagnosis[1-3]. As a core component of TCM inspection, tongue diagnosis embodies the diagnostic thinking of "inferring internal conditions from external manifestations". However, traditional tongue diagnosis heavily relies on the subjective experience and visual perception of practitioners. The vagueness of its descriptive language and the individual variability of judgment criteria have long led to inherent limitations such as low consistency and difficulty in quantification[4-6].

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In recent years, the cross-integration of information technology and traditional Chinese medicine has deepened continuously, and TCM digital diagnosis has gradually moved from theoretical conception to clinical practice. With its powerful capabilities in data processing, pattern recognition, and feature extraction, artificial intelligence provides a novel technical pathway to address the problems of "subjectivity" and "vagueness" in tongue diagnosis[7-8]. Through deep learning and intelligent analysis of massive tongue image data, AI can accurately extract microscopic indicators such as tongue color, coating thickness, and texture features, enabling objective quantification and automatic classification of tongue characteristics, thereby providing scientific and reproducible references for TCM syndrome differentiation and treatment[9]. As an important window reflecting the functional status of internal zang-fu organs, the digitization and intelligent diagnosis of the tongue have become key breakthroughs in empowering the modernization of TCM. Relevant research results are increasingly abundant, and technological iterations continue to accelerate[10].

Nevertheless, although artificial intelligence has brought new opportunities for the digital diagnosis of TCM and has strongly promoted the digital transformation of tongue diagnosis while providing solid technical support, a series of severe challenges remain to be overcome in its development and practical application[11]. TCM data exhibit significant diversity, complexity, and fuzziness. Tongue image data are particularly affected by factors such as acquisition environment, differences in device performance, and lack of unified annotation standards, which makes standardized data collection and accurate annotation extremely difficult, thereby directly and adversely affecting the training effectiveness and generalization ability of AI models[12]. Moreover, how to deeply integrate the unique theoretical system of TCM with AI technology, avoid a disconnect between technology and theory, and achieve collaborative innovation through "technological empowerment" and "theoretical guidance" remains a key issue to be urgently addressed.

Based on the above, this paper systematically reviews the current research status of AI-empowered digitalization of TCM tongue diagnosis, deeply analyzes the bottlenecks and challenges faced in the field, and on this basis discusses future development trends and technical pathways. The aim is to provide theoretical references and practical guidance for promoting the modernization, standardization, normalization, and intelligent development of TCM tongue diagnosis, and to support the inheritance, innovation, and international dissemination of traditional Chinese medicine.

2. Core Technologies and Application Status of Artificial Intelligence in Tongue Diagnosis

The comprehensive integration of artificial intelligence has established a complete technical chain comprising "image acquisition - preprocessing - tongue segmentation - intelligent feature recognition - multimodal fusion", achieving a core breakthrough in transforming TCM tongue diagnosis from subjective empirical interpretation to objective quantitative analysis. The technological evolution at each stage has jointly promoted the high-quality development of digitized tongue diagnosis.

2.1 Tongue Image Preprocessing Technology

As the foundational step in AI-empowered digitization of TCM tongue diagnosis, the image processing workflow of tongue objectification technology directly affects the accuracy of subsequent feature analysis. The tongue image preprocessing workflow typically includes key steps such as image correction, denoising, tongue segmentation, and coating-body separation. The results of tongue feature analysis obtained through the above processing have been clinically validated and confirmed to align with traditional Chinese medical theory [13–14].

In the preprocessing stage, the core tasks are to address issues such as illumination interference, color distortion, and image noise, thereby ensuring the standardization and consistency of tongue image data. To tackle color deviation under natural light conditions, early methods employed color space conversion (e.g., HSV, Lab) combined with color patch extraction from standard color cards, and used color cast correction models to calibrate the tongue region, achieving standardized calibration of tongue color and coating color features across different devices and lighting environments[15]. HU

Z X used the Canny edge detection algorithm, the findContours contour detection algorithm, and the approxPolyDP polygon fitting algorithm to automatically detect color cards, and then applied a polynomial regression color correction algorithm to correct tongue image colors[16]. WANG J S et al. proposed a tongue image color correction algorithm based on the grey wolf optimizer (GWO) to optimize a traditional BP neural network, effectively correcting tongue images captured by mobile phones[17]. To address noise, blurring, and occlusions from lips and teeth in tongue images, image processing techniques such as sparse modeling[18] and dictionary learning[19] have been used for denoising and quality enhancement, providing high-quality image data for subsequent tongue segmentation.

In the tongue segmentation stage, the core task is to accurately separate the tongue region from the background, lips, and teeth. Deep learning-based semantic segmentation algorithms have become the mainstream technology. Among them, the U-Net series, known for its excellent performance in medical image segmentation, serves as the benchmark model for tongue segmentation[20]. Based on U-Net++ (which incorporates dense skip connections and deep supervision), LIAO Z H et al. adopted a weighted cross-entropy loss function to improve tongue image segmentation[21]. Moreover, algorithms such as convolutional neural networks (CNNs)[22–23] and wavelet transforms[24] have not only enabled precise segmentation of the entire tongue region but also allowed the extraction of sub-regions (tongue tip, middle, root, and edges) as well as the sublingual veins, thereby providing accurate regional data for subsequent feature identification in specific areas.

2.2 Intelligent Recognition Algorithms for Tongue Features

Based on machine learning and deep learning algorithms, AI has achieved pixel-level, quantitative recognition of multi-dimensional tongue features, overcoming the subjective bottleneck of traditional tongue diagnosis. This represents a core component of AI-empowered digitization of tongue diagnosis. Current technologies have realized fully automated recognition and quantitative analysis of three major categories of features: tongue color and coating color, tongue shape and texture, and coating quality and moisture.

Recognition of color and coating quality. The core task is to achieve accurate classification and quantitative calculation of tongue color and coating color, which is the most mature research direction in tongue objectification. Classification models built on computer vision and machine learning can accurately detect five tongue colors (pale white, pale red, red, crimson, and purple-blue) and six coating colors (white, light yellow, yellow, burnt yellow, grey-black, and burnt black). They also enable precise zoning quantification of the tongue tip, middle, root, and edges, transforming TCM image-based thinking into computable and quantifiable mathematical models[25-26]. ZHANG Y H et al. integrated tongue coating image features with spectral information and used machine learning models to improve the accuracy and reliability of coating classification[27]. WANG E C et al. constructed a dual-branch lightweight convolutional neural network. By designing low- and high-level feature fusion modules combined with a coordinate attention mechanism, they achieved high classification accuracy with low model complexity [28].

Recognition of texture and tongue shape. Quantitative recognition and severity assessment have been realized for features such as teeth marks, fissures, pricked papillae, ecchymosis, plumpness/thinness, and tender/aged characteristics. Using blob detection, support vector machines (SVM), and K-means clustering algorithms, pricked papillae and petechiae in tongue images can be efficiently identified and extracted[29]. Tongue image analysis methods based on convolutional neural networks enable pixel-level recognition and classification of multiple features, including fissures, teeth marks, exfoliation, pricked papillae, and petechiae[30–31]. JI C P et al. introduced the attention mechanism scSE to enhance meaningful features and improve texture representation, proposing an improved tongue multi-texture detection method based on Faster R-CNN[32]. By constructing tongue image recognition models, features such as tongue shape, color, and texture can be accurately identified and quantitatively analyzed[33]. ZHANG C W extracted HSV/Lab color parameters and gray-level

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co-occurrence matrix (GLCM) texture features to establish a standardized indicator system for tongue coating color and texture[34].

2.3 Multimodal Data Fusion Technology

A single visual feature of the tongue image can no longer meet the current developmental needs; multimodal fusion and knowledge enhancement have become core directions in AI-driven tongue diagnosis. The central idea is to break the limitation of relying solely on tongue image information by integrating multiple sources of data-such as tongue image, pulse image, facial image, inquiry scales, and clinical laboratory indicators-to construct a multi-information collaborative TCM syndrome differentiation model.

Early research focused mainly on the single modality of tongue images, improving the refinement of tongue feature recognition by fusing multiple visual features including texture, color, and shape. For example, by fusing texture, color, and shape features and using machine learning models such as AdaBoost, high-performance recognition of fissured tongue was achieved[35]. Furthermore, using deep learning models to extract high-level semantic features together with low-level features (e.g., color and texture) for feature fusion offers better feature complementarity[36]. A transfer learning classification network that extracts deep features of the tongue and fuses edge features and texture features improved the classification accuracy and generalization performance of tongue image analysis[37]. LU X et al. proposed a novel model called CTSCNet, which performs feature enhancement and fusion via a multi-scale local feature enhancement module, and combines local and global features using a feature fusion module with a hybrid attention mechanism to improve recognition performance[38].

With technological advancement, researchers have gradually recognized that a single visual feature of the tongue image cannot meet the comprehensive needs of clinical syndrome differentiation, and thus multimodal fusion has emerged. YANG T et al. pointed out that the essential requirement of "four examinations combined" in TCM calls for integrating multi-source heterogeneous data including tongue image, pulse image, and inquiry data. However, traditional intelligent syndrome differentiation models mostly rely on subjective records of medical cases and lack objective multimodal information support[9]. WANG L et al. designed a TCM health status identification system that combines AI tongue diagnosis with intelligent inquiry. By fusing objectively quantified tongue features with targeted physical signs and symptom inquiry information, they constructed a multimodal health status identification model that effectively recognizes TCM health status[39]. JIANG Y L et al. discussed the translation and application of multi-parameter fusion, including TCM tongue images and clinical data, in clinical practice[40]. By fusing objective multimodal data from the four examinations, a diagnostic model for coronary heart disease with blood stasis syndrome was constructed to improve the accuracy and objectivity of TCM syndrome identification[41].

As a key technical pathway to enhance the accuracy of TCM syndrome differentiation, multimodal data fusion can fully utilize the complementary advantages of various diagnostic dimensions and effectively compensate for the one-sidedness of relying solely on tongue information for syndrome judgment. It is gradually becoming a frontier direction in intelligent tongue diagnosis research.

2.4 Application Progress of AI Technology in Intelligent TCM Diagnosis and Treatment

With the continuous maturation of core AI tongue diagnosis technologies, these technologies have gradually moved from laboratory research to clinical and public health scenarios, giving rise to three core application areas: assisted clinical diagnosis, health status identification, and treatment efficacy assessment. A number of AI-based intelligent tongue diagnosis systems have been implemented, demonstrating significant clinical and social value.

In disease-assisted syndrome differentiation, AI tongue diagnosis models have been applied to various common diseases, including chronic gastritis, coronary heart disease, diabetes mellitus, chronic kidney disease, and lung cancer. For example, in patients with chronic gastritis, models can help distinguish cold/hot and deficiency/excess patterns by assessing tongue coating thickness,

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greasiness/curdiness, and tongue color changes[42-45]. An artificial neural network (ANN)-based intelligent syndrome differentiation model has been established for chronic obstructive pulmonary disease to classify patterns[46]. In diabetes management, dynamic changes in tongue characteristics show a significant correlation with blood glucose fluctuations and complication risk, providing a quantitative basis for early intervention[47-49]. GUO D D et al. used multiple machine learning methods to establish a syndrome differentiation diagnostic model for non-small cell lung cancer (NSCLC) based on facial, tongue, and pulse data, demonstrating the high feasibility of this diagnostic model[50]. LOU J D et al. analyzed differences in tongue features among patients with different TCM patterns and used multivariate logistic regression to identify discriminating tongue indicators, finding that certain regularities exist in tongue image characteristics among postoperative colorectal cancer patients with different patterns[51].

In health status identification, AI tongue diagnosis technology is gradually being integrated into daily health monitoring and preventive medicine ("treating before illness") practices. By capturing tongue images via smart terminals, the system can output constitution types (e.g., balanced, qi-deficient, damp-heat) and viscera-bowel functional tendencies within seconds, and provide personalized health recommendations based on season and lifestyle habits. For instance, by fusing data from the four examinations and establishing predictive models, syndromes can be identified and treatment plans optimized[52]. Linking TCM tongue diagnosis with syndrome differentiation has led to the development of numerous predictive models and syndrome-element differentiation systems[53-55].

In treatment efficacy assessment, AI tongue diagnosis models, characterized by their non-invasiveness, objectivity, and traceability, have become powerful tools for evaluating TCM clinical trials and individualized treatments. By comparing multi-dimensional quantitative indicators of tongue features before and after treatment (e.g., tongue color index, coating coverage rate, fissure depth), the system can dynamically reflect pathogenesis evolution and herbal formula responses, providing visual evidence for clinical adjustment of treatment plans[56-58].

3. Challenges of AI-Empowered Digitization of Tongue Diagnosis

The rapid development of artificial intelligence has opened a new pathway for the digital transformation of TCM tongue diagnosis, driving its shift from traditional subjective qualitative judgment to objective quantitative analysis. However, in practical development and clinical application, numerous prominent challenges remain, severely restricting its large-scale implementation and high-quality development.

Insufficient data quality and standardization is the primary bottleneck. Tongue image data are significantly affected by acquisition environment, device differences, and annotation standards. Inconsistent lighting conditions and imaging parameters across different devices can easily lead to distortion of features such as tongue color and texture[59]. Tongue image annotation heavily relies on the clinical experience of practitioners and lacks unified standards; multi-center data are highly heterogeneous, and high-quality annotated data are scarce[60]. Moreover, insufficient collection of dynamic tongue images makes it difficult to fully capture the temporal changes of the tongue, directly restricting the training effectiveness and generalization ability of AI models.

Lack of AI model interpretability is a core technical challenge. Most current AI tongue diagnosis models suffer from the "black box" problem. Although they can accurately identify tongue features, they struggle to effectively associate the recognition results with TCM pathogenesis and syndrome theories, and lack diagnostic logic explanations consistent with TCM thinking. Consequently, clinical practitioners have low acceptance of model outputs, making it difficult to truly integrate these models into clinical diagnosis and treatment processes[61].

Superficial integration of TCM theory and AI technology limits development depth. Most models focus only on the extraction and classification of tongue image features, without deeply incorporating the core TCM concepts of "inferring internal conditions from external manifestations" and "pattern differentiation and treatment." They overlook the intrinsic relationships between tongue features and

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viscera-bowel states and pathogenesis, resulting in diagnostic outputs that lack TCM connotations and fail to meet the practical needs of pattern-differentiated diagnosis and treatment.

Imperfect standard systems and constraints in clinical translation and ethical compliance. Existing industry standards mainly focus on acquisition hardware, lacking specifications for algorithm performance and traceability of diagnostic results, making interoperability and mutual recognition between different devices and models difficult. At the same time, issues such as data privacy protection, diagnostic responsibility attribution, patient trust, and the absence of clinical guidelines further hinder the widespread adoption of digitized tongue diagnosis, representing key bottlenecks that urgently need to be addressed.

4. Future Development of AI-Empowered Digitization of Tongue Diagnosis

In response to the core challenges currently facing AI-empowered digitization of tongue diagnosis, and considering the development trends of artificial intelligence and the actual needs of TCM clinical practice, future research in this field will be advanced collaboratively along three major directions: standardization construction, core technology breakthroughs, and clinical translation and implementation. These efforts will promote the transition of AI tongue diagnosis from laboratory research to large-scale clinical application, achieving the modernization and intelligent transformation of traditional tongue diagnosis.

Standardization construction: consolidating the data and specification foundation. Unified standards for tongue image acquisition environment, device parameters, and annotation protocols will be established. Multi-center, high-quality, dynamic standardized tongue image databases will be constructed. At the same time, performance evaluation criteria and result traceability specifications for AI tongue diagnosis models will be formulated, promoting interoperability and mutual recognition among different devices and algorithms, thereby providing institutional guarantees for large-scale application.

Core technology breakthroughs: enhancing model interpretability. To address the “black box” problem, interpretable AI models that integrate TCM pathogenesis and syndrome theories will be developed. The knowledge of TCM tongue diagnosis theory, viscera-pattern differentiation rules, and the associations between syndrome elements and tongue features will be transformed into structured knowledge graphs[62] and embedded into the decision-making process of AI models. This will align the reasoning pathways of the models with TCM pattern differentiation logic, enabling visualization and interpretability of the model decision-making process.

Clinical translation and implementation: constructing a new paradigm of full-cycle health management. Empirical validation of AI tongue diagnosis systems in scenarios such as primary healthcare, home-based elderly care, and preventive medicine (“treating before illness”) will be promoted, and human-computer collaborative clinical decision-making processes will be established. Data privacy compliance, diagnostic responsibility attribution, and clinical guidelines will be improved to enhance the trust of both practitioners and patients. Ultimately, an intelligent health management system covering the entire spectrum of “screening - diagnosis - treatment - rehabilitation - prevention” will be built, realizing a shift from “diagnosing and treating diseases” to “full-cycle health management,” and forming a new model of integrated Chinese and Western medicine with Chinese characteristics.

5. Conclusion

The rapid advancement of artificial intelligence is driving the transformation of TCM tongue diagnosis from a traditional subjective empirical model toward objective, quantitative, and intelligent digitization. Currently, AI-based tongue diagnosis has achieved significant progress in three core scenarios: disease-assisted syndrome differentiation, health status identification, and dynamic efficacy monitoring. Deep learning-based models for tongue segmentation, feature extraction, and classification have demonstrated strong recognition performance, and some systems have already been applied clinically. However, the field still faces prominent challenges, including variable data quality, lack of annotation standards, insufficient model interpretability, superficial integration of TCM theory, and incomplete clinical norms.

To address these challenges, future efforts must be guided by TCM tongue diagnosis theory, oriented toward clinical needs, and supported by technological innovation. Multi-dimensional measures-such as establishing industry standards, developing interpretable algorithms, applying multimodal large models, improving clinical validation systems, and fostering interdisciplinary talent-will fully unleash the potential of AI in digitized tongue diagnosis. This will enable the transition from laboratory research to large-scale clinical application, and from experience-based science to data-driven evidence-based science. Ultimately, these efforts will contribute to the modernization of TCM tongue diagnosis and the construction of a new integrated Chinese-Western medicine model, better serving public health and supporting the modernization and internationalization of traditional Chinese medicine.

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