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Deep Learning in Tongue Diagnosis for Traditional Chinese Medicine: A Review

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Abstract: With the rapid development of artificial intelligence, deep learning has become an important tool in medical image analysis. Tongue image analysis is a crucial component of the objectification of tongue diagnosis in Traditional Chinese Medicine (TCM). However, traditional tongue diagnosis methods primarily rely on the experience and judgment of practitioners and can be easily influenced by external environmental factors. Therefore, the objectification and standardization of TCM tongue diagnosis has become an inevitable trend in its development. This paper systematically reviews recent research on tongue image analysis based on deep learning, discussing its achievements in tongue image processing and classification, as well as disease diagnosis. It also explores existing issues and future development directions, aiming to provide theoretical references to promote the intelligent advancement of TCM tongue diagnosis.

Keywords: Deep Learning; Tongue Diagnosis; Intelligent Diagnosis.

1. Introduction

Tongue Diagnosis in Traditional Chinese Medicine (TCM) is a time-honored diagnostic method. By observing characteristics such as tongue color, shape, and coating texture, it assists doctors in analyzing and assessing a patient's health status, making it one of the distinctive diagnostic techniques in TCM [1]. The tongue manifestations not only reflect the patient's internal health condition but also provide information related to various diseases. TCM practitioners evaluate a patient's health by examining the tongue body, including surface patterns and sublingual veins [2].

However, traditional tongue diagnosis heavily relies on the subjective experience of doctors, making the diagnostic results susceptible to individual variations among practitioners. The lack of standardized and objective criteria has limited its widespread application and promotion in modern medicine. Consequently, research on the standardization of tongue diagnosis has gained increasing attention in recent years [3]. By incorporating artificial intelligence algorithms, traditional TCM tongue diagnosis has been combined with computer image processing techniques to achieve qualitative and quantitative analysis of tongue images [4].

Nowadays, the advancement of computer science and technology has made it possible to design automated tongue diagnosis systems based on image processing and pattern recognition [5]. Machine learning algorithms, including support vector machines (SVM), random forest (RF), and principal component analysis (PCA), have been applied to study tongue image characteristics such as color, texture, and shape [6]. Traditional image classification algorithms generally perform well on simple tasks but often yield unsatisfactory results in more complex scenarios [7-8].With the rapid progress of artificial intelligence, deep learning techniques have become increasingly sophisticated, driving fundamental transformations in the field of TCM research. Liu et al. [9] employed a deep learning-based approach, using preprocessed image feature maps as network inputs, to successfully classify diabetic patients and healthy control groups. In clinical applications, many researchers have explored the standardization and quantification of tongue diagnosis and related fields. For instance, Sun [10] proposed a convolutional neural network-based method that extracts features by analyzing the entire tongue image, eliminating the constraints of fixed thresholds. This approach utilizes gradient-weighted class activation mapping for classification and generates localization maps highlighting tooth-marked regions. Experimental results demonstrate the effectiveness of this method.

Deep learning, as a crucial branch of machine learning, is based on deep neural networks and possesses powerful capabilities for automatic feature extraction and pattern recognition. In recent years, deep learning has achieved breakthrough progress in fields such as image recognition, speech processing, and natural language processing, demonstrating exceptional capabilities in handling complex data. Tongue manifestations in Traditional Chinese Medicine (TCM) are essentially image-based information, providing an ideal application scenario for deep learning technology. Introducing deep learning into TCM tongue diagnosis is expected to overcome the limitations of traditional diagnostic methods, enabling precise extraction and analysis of tongue features. This advancement will promote the modernization and intelligent development of TCM tongue diagnosis.

2. Application of Deep Learning in TCM Tongue Diagnosis

Currently, in the research on the automation of TCM tongue diagnosis, many scholars have conducted relatively mature work in various aspects such as tongue image acquisition, tongue image preprocessing, tongue segmentation, and quantification of tongue features. The main processing flow of tongue diagnosis automation can be summarized into the following steps [11]:

First, collect tongue diagnosis images and perform preprocessing, including color correction and data augmentation. Next, apply deep learning techniques for tongue segmentation and tongue feature classification. Then, infer TCM syndromes based on the TCM tongue diagnosis knowledge base. Finally, the system provides corresponding

TCM diagnostic recommendations. This workflow combines image processing and deep learning methods, aiming to improve the automation level and accuracy of tongue diagnosis.

2.1. Application of Deep Learning in Tongue Image Segmentation

Tongue image segmentation and classification are critical tasks in medical image processing, holding significant potential for application in Traditional Chinese Medicine (TCM) tongue diagnosis. Tongue segmentation is one of the most crucial steps in automated tongue diagnosis, as it isolates the tongue from the background, reducing interference from lips, teeth, and other factors, thereby improving the accuracy of tongue image classification. Early tongue segmentation methods primarily relied on image processing techniques such as edge detection and threshold segmentation. However, these approaches often performed poorly in complex environments.

In recent years, deep learning methods have demonstrated superior performance in tongue image segmentation. Li et al. [12] proposed a CNN-based framework for tongue feature classification, employing an improved facial landmark detection method and U-Net [13] to accomplish tongue segmentation. Finally, ResNet-34 was used as the backbone network to extract and classify features from tongue images, enhancing segmentation accuracy and robustness. Huang et al. [14] introduced an improved U-Net-based tongue segmentation method to address the limitations of traditional techniques in accuracy and efficiency. By optimizing the network architecture and introducing a novel loss function, their study demonstrated the superiority of this approach in tongue image segmentation through comparative experiments and quantitative analysis, showing significant improvements in segmentation precision and robustness. Yan et al. [15] utilized deep learning-based segmentation techniques to identify tongue cracks. First, tongue images were preprocessed and enhanced to improve quality. Then, a deep convolutional neural network (CNN) was designed to automatically segment crack regions in tongue images. Through extensive training on annotated data, the model was optimized, significantly improving crack recognition accuracy. Kusakunniran W [16] proposed an enhanced U-Net architecture incorporating upsampling components and multi-scale feature fusion to improve segmentation accuracy of tongue regions. The model was trained and tested on multiple tongue image datasets, demonstrating superior precision and robustness in tongue segmentation tasks. This work not only provides an effective auxiliary tool for TCM tongue diagnosis but also highlights the application potential of deep learning in medical image processing. Wu[17] developed an efficient network architecture combining Transformer and U-Net to enhance segmentation accuracy of tongue coating regions. By integrating multi-scale feature extraction and self-attention mechanisms into the input images, their method significantly improved the capture capability for complex tongue coating features. Peng[18] introduced CRANet (Convolutional Residual Attention Network), a novel model integrating CNN with attention mechanisms for simultaneous tongue segmentation and classification. The framework employs Convolutional Residual (CR) Blocks to automatically segment tongue regions, extract diagnostic features, and classify tongue images, thereby improving the objectivity and accuracy of tongue diagnosis. Experimental results confirmed CRANet's high performance in both segmentation and classification tasks, offering new technological solutions for automating TCM tongue diagnosis and promoting the integration of traditional medicine with modern computational techniques.

2.2. Deep Learning Applications in Tongue Image Classification

The complexity and fine-grained nature of tongue segmentation pose significant challenges in tongue image classification, with these two tasks being highly correlated. Xu et al. [19] proposed a multi-task joint learning model that simultaneously performs segmentation and classification of tongue images. Their deep neural network architecture processes both segmentation and feature classification tasks within a unified framework. By leveraging shared feature learning, the model effectively improves segmentation and classification accuracy while reducing training time.

Many studies on tongue image classification employ transfer learning [20-21], typically first pre-training networks on large datasets or other medical datasets. These pre-trained models are then transferred to tongue image classification tasks and fine-tuned to meet specific task requirements. Ultimately, only a small amount of medical data is needed to retrain the fully connected layers, significantly improving the network's classification performance. Chen et al. [22] proposed a similar sparse domain adaptation method for tongue diagnosis modeling, which classifies input tongue images and marks representative lesions and other abnormalities as auxiliary references for final multi-classification, effectively simulating TCM diagnosis. Wang et al. [23] initialized the network with pre-trained weights and fine-tuned it, using a ResNet-34 network structure to extract features and perform classification. This model can be generalized to images captured by other devices, demonstrating strong generalization capability, and provides an objective, convenient computer-aided tongue diagnosis method from an informatics perspective for tracking disease progression and evaluating pharmacological effects. Song et al. [24] extracted tongue features using pre-trained ResNet and Inception-v3 networks, rewriting the original network's output layer with global average pooling and fully connected layers to obtain classification results.

Deep learning models typically require large-scale tongue image datasets for training. However, certain categories of tongue images are scarce, making deep learning approaches inapplicable. Moreover, collecting extensive tongue image datasets is prohibitively costly and impractical for clinical applications. Qiu [25] proposed a novel algorithmic framework to effectively address the issue of limited data samples by leveraging meta-learning principles to enhance model learning capability under few-shot conditions. Through targeted task design and training strategies, this method can rapidly adapt to new tongue image categories while achieving high recognition accuracy with limited data. Xiao et al. [26] utilized pre-trained deep learning models to extract texture features from tongue coating images and improved classification performance via ensemble modeling. This approach effectively overcomes traditional challenges in image analysis, including insufficient data and feature extraction difficulties. Dai et al. [27] employed an autoencoder architecture to efficiently extract features from tongue images and performed concept alignment to optimize feature representation. This method automatically learns critical features in tongue images and enhances their discriminative power across different tongue classification tasks.

3. Disease Diagnosis and Classification

In disease diagnosis, researchers have employed deep learning models to identify specific diseases, such as diabetes or coronary heart disease (CHD), through tongue image analysis. Studies indicate that deep learning models demonstrate high accuracy and reliability in tongue image-based recognition and diagnosis for certain diseases.

Qiao [28] developed an intelligent tongue diagnosis model based on tongue images to improve the diagnostic accuracy of gastrointestinal diseases. This model utilizes deep learning techniques to analyze patients' tongue images, extracting and identifying features associated with various gastrointestinal disorders, including tongue coating color, shape, and texture. Research shows that this intelligent model can effectively classify and diagnose multiple gastrointestinal diseases, such as gastritis and dyspepsia, achieving high accuracy and reliability in multiple experiments. By integrating with traditional diagnostic methods, the model serves as an auxiliary decision-making tool for physicians, enhancing clinical diagnostic efficiency and accuracy. This study highlights the potential of modern technology in traditional Chinese medicine (TCM) tongue diagnosis, advancing the development of intelligent healthcare.

With recent advancements in CHD prediction systems, classification has become increasingly crucial [29], and deep learning has improved the accuracy of these systems. Li et al. [30] investigated an auxiliary diagnostic method for CHD based on tongue image features. Their approach employs deep learning for object detection, image segmentation, and feature extraction to assist in CHD diagnosis. To address data scarcity, the study further integrates text information related to tongue patterns into a multimodal network that combines textual and visual features. This innovative method enhances CHD prediction accuracy in small datasets, with experimental results showing an accuracy of 80.89% and a recall rate of 81.33%, demonstrating the feasibility and effectiveness of the proposed approach in CHD diagnosis.

Reference [31] investigated the application of the DeepNetX2 deep learning framework for diabetes diagnosis, with particular emphasis on model interpretability. The study trained the DeepNetX2 model using a dataset incorporating multiple clinical features to improve the accuracy and reliability of diabetes prediction. Additionally, techniques such as feature importance analysis and visualization tools were employed to enhance model transparency, enabling healthcare professionals to better understand the prediction rationale. Experimental results demonstrated that DeepNetX2 outperformed traditional models in diabetes diagnosis. Zhang et al. [32] addressed the challenge of diabetes detection based on sublingual vein analysis by introducing color descriptors. They proposed a multi-feature learning method incorporating the Hilbert-Schmidt Independence Criterion (HSIC) and Euclidean distance to enhance cross-modal feature representation. Their approach achieved an impressive 93.38% accuracy in diabetes detection.

Jiang et al. [33] analyzed tongue image characteristics from 1,778 participants (831 in the non-alcoholic fatty liver disease (NAFLD) group and 947 in the non-NAFLD group). By integrating quantitative tongue image features, demographic data, and serological indicators, they employed multiple neural network algorithms, including logistic regression, gradient boosting decision trees (GBDT), and adaptive boosting (AdaBoost), for NAFLD diagnosis. The logistic regression-based diagnostic model achieved the best fusion performance, attaining an 81.70% accuracy.

Traditional Chinese Medicine constitution (TCMC), as one of the important components of TCM theory, has attracted increasing attention from researchers. Reference [34] investigated automatic TCM syndrome identification by extracting features from multi-perspective tongue images combined with deep learning methods. The study first collected tongue images from different angles, extracted multiple features such as tongue body color, shape, and coating thickness, and integrated this information using feature fusion techniques to improve recognition accuracy. Experimental results showed that this method significantly outperformed traditional single-perspective analysis in both accuracy and stability for syndrome identification, demonstrating its potential application value in TCM diagnosis and providing new insights for future intelligent diagnostics. However, in actual constitution assessment, individuals often exhibit two or more overlapping constitutions. Li et al. [35] adopted a multi-label classification method to identify compound constitutions in tongue diagnosis images and compared the feature extraction performance of different networks. Jiang et al. [36] conducted image quality assessment on tongue diagnosis images, followed by color correction and tongue segmentation. They extracted and analyzed features including tongue color, texture, and shape, performed constitution classification by integrating these tongue image features, and finally developed TCM treatment plans based on the classification results.

4. Challenges and Issues

4.1. Data Quality and Scale

TCM tongue diagnosis faces significant challenges in standardized data collection. Variations in imaging devices, environmental conditions, and capture angles lead to inconsistent data quality, adversely affecting the training performance of deep learning models. Additionally, annotating tongue images requires specialized TCM knowledge, which introduces subjectivity and inter-annotator variability due to the lack of unified labeling standards. This further compromises the accuracy and reliability of the data. Moreover, the current dataset size remains relatively small, failing to meet the demand for large-scale data in deep learning, thereby limiting model generalization and performance improvement.

4.2. Model Interpretability

Deep learning models are often regarded as "black boxes," with decision-making processes that are difficult to interpret. This opacity reduces trust among doctors and patients in the diagnostic results, hindering the clinical adoption of deep learning technology. Therefore, increased efforts should be directed toward interpretability research, exploring effective explainable algorithms and tools to help clinicians better understand model decisions, thereby improving acceptance and trust in AI-assisted systems.

4.3. Integration with TCM Theory

Currently, deep learning models in tongue diagnosis applications tend to focus on data-driven analysis while lacking deep integration with TCM theory. This limits the ability to fully uncover the underlying TCM pathological mechanisms reflected in tongue features. Future research should emphasize incorporating TCM theoretical knowledge into deep learning models to provide theoretical explanations for tongue analysis results, promoting both the preservation and innovation of TCM tongue diagnosis.

5. Future Development Trends

5.1. Multimodal Data Fusion and Deep Learning Integration

Future research will focus on integrating multimodal data such as tongue images and pulse signals, leveraging deep learning for comprehensive analysis to obtain more holistic health information and improve the accuracy and reliability of tongue diagnosis. Additionally, novel model architectures and algorithms need to be explored to address feature alignment and fusion challenges across different data modalities.

5.2. Cross-Disciplinary Collaboration and Clinical Practice Implementation

Efforts will be intensified to foster collaboration among TCM, computer science, and biomedical engineering, integrating expertise and technologies from these fields to advance the development and innovation of deep learning in TCM tongue diagnosis. Large-scale clinical studies will be conducted to validate the efficacy and safety of deep learning applications in tongue diagnosis, while establishing relevant clinical standards and guidelines to facilitate widespread adoption in medical practice.

5.3. Development of Intelligent Tongue Diagnosis Devices

By combining deep learning technology, portable and intelligent tongue diagnosis devices will be developed to enable rapid data acquisition, real-time analysis, and immediate feedback. These devices will empower patients to perform self-monitoring at home and expand the application of TCM tongue diagnosis to primary healthcare and family health management. Furthermore, the integration of intelligent tongue diagnosis devices with telemedicine and mobile healthcare will be explored, providing technical support for remote TCM diagnostics.

6. Summary

Deep learning technology has brought new opportunities for the modernization of Traditional Chinese Medicine (TCM) tongue diagnosis, achieving significant progress in areas such as tongue feature extraction and disease diagnosis. However, challenges remain in data quality, model interpretability, and theoretical integration. Moving forward, continued exploration and innovation in multimodal data fusion, cross-disciplinary collaboration, and intelligent device development are expected to further enhance the application of deep learning in TCM tongue diagnosis. This will promote its broader adoption in modern medicine while preserving and advancing this traditional diagnostic approach.

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