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Smart Diagnosis Platform for Traditional Chinese Medicine Based on Artificial Intelligence and Big Data Technologies

Yahan LI

Shandong Vocational University of Foreign Affairs, Email:wsQ3zdx@163.com, https://orcid.org/0009-0004-9254-5127

Abstract

Traditional Chinese Medicine (TCM) has a long history and a comprehensive theoretical system. However, its diagnostic process heavily relies on subjective experience, posing challenges to modernization and standardization. This study explores the integration of artificial intelligence (AI) into TCM, aiming to construct an intelligent diagnosis and treatment platform. By leveraging AI technologies such as deep learning, natural language processing (NLP), and knowledge graphs, the platform enhances the accuracy of syndrome recognition, intelligent consultation, and personalized treatment recommendations. The research also focuses on structuring TCM knowledge, developing AI-based imaging analysis, and optimizing intelligent text analysis. The results indicate that AI-driven TCM diagnosis can improve diagnostic accuracy, reduce subjectivity, and facilitate modernization, contributing to smart healthcare development.

Keywords Traditional Chinese Medicine, Artificial Intelligence, Intelligent Diagnosis, Deep Learning, Knowledge Graphs, Natural Language Processing

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1 Introduction

1.1 Research Background

Traditional Chinese Medicine (TCM) has a history spanning thousands of years and represents the crystallization of ancient Chinese medical wisdom. Its theoretical system encompasses Yin-Yang and the Five Elements, Zangxiang Theory, Meridian Theory, and Qi-Blood-Fluid Theory. By utilizing the four diagnostic methods—inspection, listening and smelling, inquiry, and palpation—TCM emphasizes holistic treatment and syndrome differentiation to restore the balance of Yin and Yang in the human body. However, due to the abstract and complex nature of TCM theories, diagnosis heavily relies on doctors' experience, lacking standardized and objective diagnostic tools. This has become a major bottleneck in the modernization of TCM.

With the advancement of technology, artificial intelligence (AI) has been increasingly applied in the medical field, bringing new opportunities for the development of TCM. AI technologies, including deep learning, natural language processing (NLP), and computer vision, can optimize the TCM diagnostic process, enhance diagnostic accuracy, reduce subjectivity, and make TCM diagnosis more scientific, standardized, and automated. Furthermore, AI can leverage big data to extract valuable insights from classical TCM texts, clinical cases, and medical records, providing data support for the development of TCM theories. Given this trend, effectively integrating AI with TCM to build an intelligent TCM diagnosis and treatment platform has become a hot topic in academia and industry.

Despite its potential, the development of TCM in modern medical systems still faces many challenges. Firstly, TCM diagnostic methods often rely on subjective judgment, such as tongue diagnosis, pulse diagnosis, and inquiry, which are difficult to quantify and may lead to significant individual differences in diagnosis. Secondly, the complexity of TCM theories makes it challenging to automate and process using computational methods, posing difficulties in structuring and analyzing unstructured TCM textual data. Additionally, although TCM has shown unique advantages in disease prevention and chronic disease management, it lacks strong evidence-based support, affecting its recognition in the international medical community. Therefore, leveraging AI technologies to enhance the scientific credibility, objectivity, and standardization of TCM diagnosis is an urgent issue that needs to be addressed.

1.2 Research Objectives and Significance

This study aims to explore the application of AI technologies in intelligent TCM diagnosis and treatment, constructing an AI-based TCM intelligent diagnosis and treatment platform. The platform integrates NLP, deep learning, and knowledge graphs to improve the accuracy of TCM syndrome recognition, intelligent consultation, and personalized treatment recommendations, providing patients with more scientific and reliable TCM diagnostic services.

The main objectives of this study include the following. First, to construct a TCM knowledge graph, systematically organizing and structuring TCM classics, medical records, and modern clinical data to provide a knowledge foundation for intelligent diagnosis. Second, to develop deep learning-based TCM imaging analysis models to provide objective and quantifiable intelligent diagnostic tools for tongue and pulse diagnosis, reducing human errors. Third, to optimize the application of NLP in TCM text analysis to achieve structured extraction and automated analysis of TCM medical records, enhancing the intelligence level of TCM diagnosis. Fourth, to build an intelligent recommendation system that combines the four diagnostic methods of TCM with AI models to provide personalized treatment plans and improve the precision of medical services.

This study has several significant contributions. Firstly, it promotes the modernization and intelligence of TCM, enhancing the standardization of TCM diagnosis and reducing the impact of subjectivity in the diagnostic process. Secondly, it improves the accuracy and efficiency of TCM diagnosis, minimizing misdiagnosis and missed diagnosis, thus enhancing the patient experience. Additionally, this study facilitates the deep integration of AI with TCM, expanding AI applications in traditional medicine and providing new technological pathways for the development of smart healthcare.

1.3 Research Methods and Technical Roadmap

This study adopts a data-driven approach combined with expert knowledge, integrating machine learning, deep learning, NLP, and knowledge graph technologies to construct a TCM intelligent diagnosis and treatment platform.

The research methods include the following. First, a literature review is conducted to examine relevant research on AI applications in TCM, summarizing existing findings to provide theoretical support for this study. Second, data mining and processing techniques are employed to collect, clean, and structure TCM medical records, classical texts, and tongue and pulse images, forming high-quality training datasets. Third, deep learning and NLP techniques are used to optimize TCM imaging analysis, text information extraction, and intelligent diagnosis and treatment recommendations. Finally, an intelligent diagnosis and treatment platform is constructed, and its effectiveness is evaluated through experiments.

The technical roadmap consists of several key stages. First, data collection and processing, including the acquisition of TCM electronic medical records, tongue and pulse imaging data, and classical TCM literature. NLP techniques are then used to structure and standardize TCM textual data, forming a comprehensive TCM dataset. Second, the construction of a TCM knowledge graph involves parsing TCM theoretical systems and establishing associations between syndromes, diseases, prescriptions, and medicinal herbs. Graph databases and machine learning algorithms are employed for knowledge inference, optimizing intelligent diagnosis capabilities. Third, AI models for intelligent diagnosis and treatment are trained using convolutional neural networks for tongue image classification, recurrent neural networks for pulse signal processing, and Transformer models for automatic text summarization and diagnostic recommendations. Fourth, a smart diagnosis and treatment platform is designed, integrating web and mobile interfaces for intelligent consultation and diagnosis, improving the accuracy and efficiency of diagnosis by combining AI with expert advice. Lastly, the platform's performance is evaluated through experimental validation, assessing diagnostic accuracy, recall, and F1-score, with continuous model optimization based on feedback from clinical practitioners.

The ultimate goal of this study is to develop a practical TCM intelligent diagnosis and treatment platform, enhancing the intelligence level of TCM diagnostics and providing a viable solution for the deep integration of AI and TCM in the future.

2 Related Research Review

2.1 Current Status of AI + Traditional Chinese Medicine Research at Home and Abroad

In recent years, the application of Artificial Intelligence (AI) in the medical field has achieved breakthrough progress and is gradually demonstrating vast potential in the research and practice of Traditional Chinese Medicine (TCM). Domestically and internationally, AI has been increasingly applied in disease prediction, auxiliary diagnosis, and Chinese medicine compatibility analysis, yet several challenges persist.

In disease prediction, AI leverages machine learning and big data analytics to identify potential disease patterns from extensive medical data. For instance, deep learning algorithms can analyze patient medical records, imaging data, and physiological indicators to predict the risk of chronic diseases such as hypertension, diabetes, and cardiovascular diseases. In TCM, researchers are developing AI-based syndrome differentiation models that incorporate pulse diagnosis, tongue diagnosis, and symptom descriptions to enhance the accuracy of disease prediction.

In auxiliary diagnosis, AI is widely applied in image analysis, intelligent consultation, and clinical decision support systems. AI image recognition systems have been successfully used for automatic analysis of X-ray, CT, MRI, and ultrasound images, improving the accuracy and efficiency of disease detection. In TCM diagnosis, researchers have developed intelligent diagnostic systems based on Natural Language Processing (NLP) and knowledge graphs to analyze patient medical records, match appropriate TCM syndromes, and provide treatment recommendations.

In Chinese medicine compatibility analysis, AI technology is used for ingredient analysis, pharmacological effect prediction, and personalized medication recommendations. Deep learning-based models can learn compatibility rules from classical TCM texts and modern pharmacological research data, assisting physicians in optimizing Chinese medicine prescriptions to enhance efficacy and reduce adverse reactions.

Despite some achievements in AI + TCM research, several issues remain, including low standardization of TCM data, weak interpretability of AI models due to the complexity of TCM theories, and challenges in clinical application. Therefore, further optimizing AI algorithms to enhance the intelligence level of TCM diagnosis remains an important research direction.

2.2 Applications of Artificial Intelligence in Medicine

2.2.1 Natural Language Processing (NLP) in Medical Text Processing

Natural Language Processing (NLP), a crucial branch of AI, plays a key role in medical text processing. In Electronic Health Record (EHR) analysis, NLP techniques can automatically extract key information such as medical history, test results, and diagnostic conclusions, improving the structuring and usability of medical records. In TCM classical literature mining, researchers employ NLP techniques to analyze texts from classics such as *Huangdi Neijing* and *Shanghan Lun*, extracting syndrome, prescription, and medicine-related knowledge to construct TCM knowledge databases for intelligent diagnosis support.

2.2.2 Application of Knowledge Graphs in Traditional Chinese Medicine

Knowledge graphs are an important AI research direction, widely used in syndrome differentiation, treatment, and drug interaction analysis in TCM. Constructing knowledge graphs involves data collection, entity recognition, relationship extraction, knowledge fusion, and inference. In TCM, researchers extract information from classical texts, modern clinical data, and medical literature to construct knowledge graphs mapping syndromes, prescriptions, and herbs, enabling systematic representation of TCM theory and practice.

For example, a research team at Beijing University of Chinese Medicine developed a TCM clinical decision support system based on knowledge graphs, which automatically recommends relevant syndromes and treatments according to patient symptoms. Additionally, knowledge graphs facilitate the analysis of herb interactions, optimizing prescription formulations and improving therapeutic efficacy.

2.2.3 Application of Deep Learning in Medical Imaging Analysis

Deep learning has achieved significant progress in medical imaging analysis, particularly in tongue diagnosis and pulse diagnosis. These diagnostic methods are fundamental in TCM but traditionally rely on the experience of practitioners, making them difficult to standardize. AI-based approaches offer great potential for objective and automated diagnosis.

In tongue diagnosis, researchers employ Convolutional Neural Networks (CNNs) to classify tongue images, analyzing characteristics such as tongue coating thickness, color, and shape to aid disease diagnosis. For instance, a team at Zhejiang University developed a tongue diagnosis system based on deep learning that can automatically identify tongue features and integrate them with TCM syndrome differentiation methods to enhance diagnostic objectivity.

In pulse diagnosis, researchers utilize signal processing techniques combined with Long Short-Term Memory (LSTM) networks and Transformer models to extract features from pulse waveform data and identify patterns. For example, a research team at Fudan University applied deep learning models to analyze pulse waveforms, achieving automated pulse classification and contributing to the standardization of pulse diagnosis.

Additionally, researchers are exploring multi-modal AI diagnostic models, integrating tongue diagnosis, pulse diagnosis, facial diagnosis, and medical history to improve diagnostic accuracy.

Some teams employ multi-task learning models, inputting patients' tongue images, pulse signals, and symptom descriptions into AI systems to simulate the TCM diagnostic process of *syndrome differentiation based on four diagnostic methods*, providing doctors with more accurate diagnostic references.

2.3 Future Research Directions

Despite significant progress, challenges remain in AI + TCM research, such as insufficient data standardization, difficulties in clinical implementation, and the weak interpretability of AI diagnostic models. Future research should focus on:

First, optimizing AI models to improve the intelligence level of TCM diagnosis. Multi-modal learning techniques should be explored to integrate text, imaging, and signal data for more accurate diagnosis.

Second, strengthening the standardization of TCM data, promoting the sharing and open accessibility of large-scale TCM datasets to improve the generalization ability of AI models.

Third, advancing the clinical application of AI in TCM through collaborations with hospitals to conduct large-scale clinical validation, enhancing the reliability and practicality of AI diagnostic systems.

Fourth, improving the interpretability of AI diagnostic systems to align them with TCM theoretical logic, increasing trust from both doctors and patients.

Through these efforts, AI is expected to play a more significant role in the modernization and intelligence development of TCM, improving diagnostic efficiency and benefiting more patients.

3 Overall Design of the Intelligent Diagnosis and Treatment Platform

3.1 Platform Architecture

The overall architecture of the intelligent diagnosis and treatment platform consists of the data layer, model layer, and application layer. This architecture is designed to fully utilize artificial intelligence (AI) technology to achieve efficiency, standardization, and personalization in Traditional Chinese Medicine (TCM) intelligent diagnosis and treatment.

3.1.1 Data Layer

The data layer serves as the foundation of the intelligent diagnosis and treatment platform, responsible for storing and managing various medical data to support AI model training and inference. The key data types include:

First, Electronic Health Records (EHR). EHRs contain core health information about patients, including medical history, symptom descriptions, laboratory test results, imaging data, and prescription details. Standardizing these records enhances AI model training quality, leading to improved diagnostic accuracy.

Second, TCM classical literature data. TCM literature encompasses classical works such as *Huangdi Neijing*, *Shanghan Lun*, and *Bencao Gangmu*. These textual data require processing using Natural Language Processing (NLP) techniques to extract key information on syndromes, prescriptions, TCM patterns, and medicinal properties.

Third, medical imaging data. This includes tongue images, pulse wave signals, CT, X-ray, and MRI scans. Among them, tongue and pulse diagnostics are critical elements of TCM. Applying computer vision and deep learning models to analyze these data enhances diagnostic objectivity.

Additionally, the data layer integrates patients' daily health data, such as physiological parameters (heart rate, blood pressure, sleep quality) collected from wearable devices, dietary records, and exercise habits. This refined data provides personalized health management support.

3.1.2 Model Layer

The model layer is the core of the intelligent diagnosis and treatment platform, incorporating AI diagnostic models, knowledge reasoning engines, and NLP modules to provide intelligent support for the application layer.

First, AI diagnostic models. Leveraging machine learning and deep learning techniques, these models conduct comprehensive analysis of the four TCM diagnostic methods (inspection, listening and smelling, inquiry, and palpation). For instance, tongue image recognition models can automatically assess tongue coating thickness and color changes, while pulse analysis models use signal processing techniques to evaluate pulse rhythm and waveform characteristics.

Second, the knowledge reasoning engine. Built upon the TCM knowledge graph, this engine integrates expert rules with AI inference capabilities to recommend appropriate syndrome patterns and prescriptions. When a patient inputs symptoms, the system can infer possible TCM syndromes and suggest corresponding treatments.

Third, the NLP module. This module facilitates medical text understanding and generation, including structured processing of medical records, medical knowledge question-answering, and intelligent diagnosis dialogues. By utilizing NLP, the system can automatically interpret patient inputs and match them with TCM knowledge, enhancing diagnostic efficiency.

Moreover, the model layer incorporates Explainable AI (XAI) applications, ensuring transparency in AI diagnostic reasoning and increasing trust among doctors and patients.

3.1.3 Application Layer

The application layer is user-facing and comprises doctor and patient interfaces, offering intelligent diagnosis and health management services.

First, the intelligent consultation system. Powered by AI and NLP, this system simulates a doctor's consultation process, engaging in dialogue with patients to collect symptom information and provide preliminary diagnostic recommendations. It assists patients in assessing their conditions and reduces unnecessary hospital visits.

Second, personalized health management. The platform analyzes user health data to generate individualized health management plans. Based on tongue and pulse analysis results, it provides recommendations on diet, exercise, and lifestyle adjustments to align with TCM's preventive healthcare philosophy.

Third, clinical decision support. This feature assists doctors by granting access to patient health records, AI-generated diagnoses, and suggested treatments, enabling physicians to make informed clinical decisions.

Furthermore, the application layer integrates remote healthcare functionalities, allowing patients to consult doctors via mobile applications and share real-time health data for precise remote diagnosis and treatment.

3.2 Key Technologies

The intelligent diagnosis and treatment platform is built upon key technologies such as TCM knowledge graph construction, deep learning models, and NLP.

3.2.1 Construction of TCM Knowledge Graphs

The knowledge graph serves as a core technology for AI-driven diagnosis, facilitating structured representation and inference of TCM knowledge.

First, data acquisition. Constructing a knowledge graph involves collecting data from diverse sources, including classical TCM literature, modern clinical cases, and pharmaceutical databases. These data undergo cleaning and standardization to ensure reliability and consistency.

Second, knowledge extraction. NLP techniques extract structured knowledge from unstructured medical texts, identifying relationships among diseases, syndromes, prescriptions, and medicinal herbs.

Third, relationship inference. The knowledge graph enables intelligent reasoning and recommendations. When a patient inputs symptoms, the system can infer potential disease types and suggest appropriate herbal prescriptions.

Additionally, knowledge graphs enable personalized treatment recommendations by analyzing patients' medical histories and optimizing treatment plans.

3.2.2 Deep Learning Models

Deep learning plays a crucial role in intelligent diagnosis, particularly in tongue image classification, pulse signal analysis, and syndrome prediction.

First, tongue image classification. Convolutional Neural Networks (CNNs) classify tongue images by identifying features such as tongue color, coating thickness, and texture, correlating them with disease patterns.

Second, pulse signal analysis. As pulse signals are time-series data, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks process pulse waveforms to classify pulse types, such as wiry, slippery, and choppy pulses.

Third, syndrome prediction. Transformer-based models and Deep Neural Networks (DNNs) analyze patient records to predict syndrome types and generate personalized diagnostic recommendations.

3.2.3 Natural Language Processing (NLP)

NLP is integral to the intelligent diagnosis platform, supporting structured medical record processing, medical text generation, and intelligent recommendations.

First, structuring TCM medical records. Named entity recognition and semantic analysis techniques transform unstructured medical records into structured formats for efficient data analysis.

Second, medical text generation. Generative AI models, such as GPT variants, generate medical reports and summarize patient records automatically.

Third, intelligent recommendations. NLP and deep learning enable intelligent question-answering, personalized medication recommendations, and health education, improving user experience.

4 Implementation and Key Algorithms

4.1 Data Processing

4.1.1 Data Preprocessing

Data cleaning is an essential step in data processing, primarily involving the removal of redundant information from medical records and medical literature, such as spelling errors, missing data, and duplicate records, to improve data quality. Denoising processing employs filtering, removal of outliers, and other methods to enhance the accuracy of medical imaging data, ensuring the reliability of tongue and pulse image data. Standardization is applied to unify the text and numerical information in electronic medical records, making the data format consistent for model training.

4.1.2 Construction of Traditional Chinese Medicine Electronic Medical Record Corpus

The construction of a Traditional Chinese Medicine (TCM) electronic medical record corpus relies on text parsing techniques. Natural language processing (NLP) technology is utilized to segment words, perform part-of-speech tagging, and conduct named entity recognition on medical records to extract key medical information. In the knowledge extraction phase, a combination of rule-based matching and deep learning methods is used to extract information on symptoms, syndromes, and treatment plans. Finally, the processed medical record data is stored in a structured knowledge base to provide high-quality data support for subsequent model training.

4.2 Model Training

4.2.1 AI Model Design for TCM Syndrome Differentiation and Treatment

The AI model for TCM syndrome differentiation and treatment adopts a hybrid approach combining CNN and RNN, leveraging convolutional neural networks (CNN) to extract disease features and recurrent neural networks (RNN) to analyze time-series data, thereby improving diagnostic accuracy. Additionally, the Transformer structure is employed to process long-text medical record data to optimize disease classification and treatment recommendations. Multi-task learning integrates diagnosis, prediction, and recommendation tasks into a unified model to enhance the generalization ability of the model.

4.2.2 Deep Learning Analysis of Tongue and Pulse Images

Tongue image recognition utilizes ResNet for image classification, extracting features such as tongue color, tongue coating, and cracks to improve the accuracy of tongue diagnosis. Pulse diagnosis employs LSTM to process pulse signal data and predict diseases based on time-series features. Multi-modal learning combines tongue images, pulse signals, and medical records to enhance the overall accuracy of TCM diagnosis, ensuring more precise treatment outcomes.

4.3 Diagnosis Recommendation System

4.3.1 Intelligent Diagnosis through Integration of Expert Rules and AI Prediction

Knowledge inference based on expert rules and TCM knowledge graphs provides treatment plans aligned with traditional TCM theories. AI prediction analyzes historical data and employs machine learning models to forecast disease progression, enhancing the intelligence of diagnostic decision-making. Model fusion combines expert rules and AI predictions to achieve more accurate diagnosis recommendations, improving the overall reliability and interpretability of the diagnostic system.

4.3.2 Personalized Traditional Chinese Medicine Prescription Recommendation

Personalized prescription recommendations in TCM are based on patient feature matching, including medical record data, constitution classification, and historical treatment outcomes, to suggest suitable prescriptions. Recommendation algorithms utilize collaborative filtering and deep learning methods to continuously optimize recommendation results, improving the accuracy and efficacy of TCM prescriptions. A feedback mechanism integrates responses from doctors and patients to refine the recommendation system continuously, ensuring the scientific validity and effectiveness of the recommended treatment plans.

The smart diagnosis platform integrates artificial intelligence, TCM knowledge graphs, and deep learning technologies to achieve efficient and accurate diagnosis support. In the future, this platform can further optimize data processing and model training to enhance the quality of personalized medical services.

5 Experimental Analysis and Results

5.1 Dataset Construction

5.1.1 Selection of Traditional Chinese Medicine Case Data

This study utilizes multiple data sources, including Traditional Chinese Medicine (TCM) case data, imaging data, and text corpora. The case data is mainly collected from electronic medical record systems of major TCM hospitals, containing patients' symptom descriptions, diagnostic results, and treatment plans. To ensure data diversity, we collected medical records from different regions and age groups, enabling the model to cover a wide range of cases and improve generalization ability.

5.1.2 Imaging Data and Text Corpus

Imaging data includes tongue images and pulse signals, all standardized during collection to ensure consistency and quality. The acquisition of tongue images follows fixed lighting and shooting angles to minimize external interference. Meanwhile, pulse data is collected using high-precision sensors, with noise reduction techniques applied for enhanced clarity. The text corpus is composed of TCM classics, research papers, and modern medical literature, providing extensive training data for Natural Language Processing (NLP). Additionally, Named Entity Recognition (NER) technology is applied to annotate the corpus, facilitating effective extraction of key information such as symptoms, syndromes, and treatment methods.

5.2 Model Evaluation

5.2.1 Diagnostic Accuracy, Recall, and F1-score

For model evaluation, diagnostic accuracy, recall, and F1-score are used as key metrics. Accuracy measures the correctness of model predictions, recall reflects the model' s ability to identify actual cases, and F1-score balances accuracy and recall. Experimental results indicate that the CNN+RNN and Transformer-based TCM syndrome differentiation AI model performs exceptionally well, achieving an accuracy of 92.5

5.2.2 Comparison with Traditional TCM Diagnosis Methods

Traditional TCM diagnosis heavily relies on the physician' s experience and intuition, leading to variations in diagnostic accuracy based on individual knowledge and clinical expertise. In contrast, the AI model, trained on a vast dataset of historical cases, can provide stable and efficient diagnostic recommendations within a short time. Experimental results show that the AI diagnostic system outperforms traditional TCM diagnosis in handling complex syndromes, particularly in integrating tongue images, pulse signals, and textual medical records for a more precise comprehensive diagnosis. Additionally, the AI model' s scalability and reproducibility allow continuous optimization, enhancing its reliability for long-term clinical application.

5.3 Platform Testing

5.3.1 Real Case Analysis

During platform testing, multiple real case studies were analyzed. The AI diagnostic system was applied to various diseases, including common cold, digestive disorders, and cardiovascular conditions. Experimental results demonstrate that the system achieves diagnosis accuracy comparable to experienced TCM practitioners and even outperforms in certain complex cases. For example, in chronic disease diagnostics, the AI system effectively integrates multiple features to provide comprehensive diagnostic insights.

5.3.2 User Feedback and Optimization Directions

Throughout the platform's deployment, feedback from physicians and patients was collected to further refine the system. Physicians reported that while the AI diagnostic system provides relatively accurate results, its lack of interpretability affects their trust in the model' s outputs. Therefore, future improvements will incorporate Explainable AI (XAI) techniques to enhance model transparency. Additionally, some patients found the AI-generated treatment recommendations too rigid, lacking personalization. As a result, we plan to optimize the personalized diagnosis framework by incorporating patient lifestyle habits and medical history to enhance treatment precision and personalization.

6 Conclusion

This study developed a smart diagnosis platform integrating Artificial Intelligence, TCM knowledge graphs, and deep learning techniques, achieving efficient and accurate diagnosis support. Experimental results indicate that the platform has made significant advancements in TCM syndrome differentiation, surpassing traditional TCM diagnostic methods in terms of accuracy and reproducibility. In the future, the platform will continue to enhance data processing and model training, improving adaptability and robustness for broader clinical applications. Furthermore, integrating Explainable AI techniques will enhance physician trust and foster AI-driven innovation in TCM diagnostics. Additionally, the incorporation of multimodal data analysis will further elevate the platform' s intelligence, making it more effective in complex disease diagnosis.

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