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Research on the Construction Method of Famous TCM Physicians' Academic Knowledge Graph Based on Multimodal Deep Learning — Application of the AGBAN Model

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Abstract: Aiming at the problems of knowledge fragmentation and opaque reasoning in the digital inheritance of famous TCM physicians' academic thoughts and diagnosis-treatment experience, a multimodal knowledge graph construction method based on the AGBAN model is proposed. Using more than 3,000 outpatient medical records of famous TCM physicians as the data source, multimodal information is integrated to construct a clinical knowledge graph through ontology design, entity-relationship extraction, and knowledge storage. The graph attention network and reinforcement learning mechanism of the AGBAN model are introduced to optimize the diagnosis-treatment path. The results show that the knowledge graph contains 3,089 entities and 1,461 relationships, with an average degree of 2.49; the average reciprocal rank of link prediction of the AGBAN model is 0.973, which is 165.4% higher than that of the TransE model, the diagnosis success rate is 59.19%, and the average reasoning path is 5 steps; cluster analysis verifies the core TCM principles such as "drug-syndrome correspondence". The conclusion indicates that this method realizes the structured representation and intelligent reasoning of famous TCM physicians' clinical experience, providing a feasible path for TCM academic inheritance and clinical decision support.

Keywords: Multimodal deep learning; Knowledge graph; AGBAN model; Inheritance of famous TCM physicians' experience; Clinical reasoning

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1. Introduction

1.1. Research background and significance

With the wide application of hospital information systems and electronic medical records, a large amount of diagnosis-treatment data of famous TCM physicians has been accumulated. However, such data is mostly stored in fragmented “record-field” forms, lacking explicit modeling of semantic relationships between core elements such as “symptoms-syndromes-prescriptions”, which is prone to forming data silos. Existing analysis methods mostly stay at the basic statistical level, making it difficult to support in-depth association mining and causal inference, resulting in insufficient interpretability of diagnosis-treatment experience and limited inheritance efficiency.

The State Administration of Traditional Chinese Medicine has issued a number of policies to promote TCM teacher-apprentice inheritance, and has selected 3,404 instructors and trained 6,562 successors [1,2]. However, traditional teacher-apprentice inheritance has problems such as low efficiency, difficulty in knowledge management, and limited scope. As a national demonstration pilot city for the inheritance and innovative development of traditional Chinese medicine, Zhongshan urgently needs scientific methods to support the digital preservation and intelligent application of famous TCM physicians’ experience.

1.2. Research status at home and abroad

Knowledge graphs construct a semantically interconnected knowledge network with “entity-relationship” triples as the basic unit, providing an effective framework for integrating multi-source heterogeneous clinical data of famous TCM physicians. In recent years, Yang Haici from Peking University and others used knowledge graph technology to construct the academic inheritance ontology of the Song Dynasty, and Chen Yingxuan from Guangzhou University of Chinese Medicine and others constructed the knowledge graph of TCM ancient books based on the original text of *Lingshu*, verifying the application potential of knowledge graphs in the field of TCM [3,4]. However, traditional knowledge graphs still face important challenges in the diagnosis-treatment reasoning process, insufficient reasoning transparency and interpretability, especially in clinical decision-making, it is difficult to effectively solve the problem of “drugs not matching syndromes”.

With the development of multimodal learning, integrating multi-source data such as text, images, and videos has become an important direction to improve knowledge representation capabilities. The AGBAN (Attention-guided Graph Neural Network for Multi-modal Data Representation Learning) model, proposed by the Institute of Automation, Chinese Academy of Sciences, combines graph neural networks and attention mechanisms, which can effectively handle the association and interaction between different modal data, providing a new theoretical framework for the construction of multimodal knowledge graphs [5].

1.3. Research objectives and innovations

This study aims to solve the deficiencies of current TCM knowledge graphs in reasoning transparency and interpretability, propose a multimodal knowledge graph construction method based on the AGBAN model, and realize the modeling of complete knowledge links from symptoms to treatment plans. The main innovations include: first, integrating text and image information in the outpatient medical records of famous TCM physicians to construct multimodal knowledge representation; second, introducing attention-enhanced graph neural networks and reinforcement learning mechanisms to realize adaptive learning and reasoning optimization of diagnosis-treatment paths; third, constructing the causal structure of “symptoms → core pathogenesis → syndromes → prescriptions” through a path planning model to improve the reasoning transparency of intelligent diagnosis systems [6].

2. Methods and technologies

2.1. Overview of research process

Integrate more than 3,000 anonymized TCM outpatient medical records from Zhongshan Hospital of Traditional Chinese Medicine from 2022 to 2024, and construct a clinical TCM knowledge graph containing 3,089 entities and 1,461 relationships through data preprocessing, ontology design, knowledge extraction, knowledge storage and other steps, using Neo4j graph database for storage; on this basis, apply the graph attention network and reinforcement learning mechanism of the AGBAN model to simulate the cognitive process of famous TCM physicians and realize the optimization of diagnostic reasoning [7].

2.2. Data source and preprocessing

The research data are outpatient medical records from the famous TCM physician studio of Zhongshan Hospital of Traditional Chinese Medicine, covering full-process information such as main complaints, diagnoses, syndromes, and prescriptions. Clinical logical rules are used to evaluate data quality, checking the consistency between gender, age and diagnosis, and the matching degree between tongue signs and syndromes. The proportion of logical conflict records is less than 10%, and the data quality is reliable after expert review.

Data preprocessing adopts a dual-feature lexicon method to classify integrated TCM-WM prescriptions; regular expressions are used to parse TCM names, extract the “name-dose-unit” pattern, hierarchically clean WM names, and remove dosage form and trade name annotations [8].

2.3. Knowledge extraction

2.3.1. Entity extraction

Combined with the structured characteristics of clinical Excel tables, seven types of entities are defined: TCM disease names, TCM syndromes, symptoms, signs, TCM medicines, WM medicines, and tongue sign features. The indication function of table headers and table names is used to improve extraction accuracy, and a total of 3,089 entities are extracted.

2.3.2. Attribute extraction

Identify attribute-value pairs of entities and convert them into edges of the knowledge graph. For example, extract attributes such as tongue color and tongue shape from the “tongue signs” column to form “entity-attribute-value” triples.

2.3.3. Relationship extraction

A rule-based method is adopted to define seven types of entity relationships, such as “symptoms point to syndromes”, “syndromes are treated with TCM medicines”, and “diseases are treated with WM medicines”, and finally 1,461 relationship edges are constructed [9].

2.4. Knowledge graph storage and update

The Neo4j graph database is used to store the knowledge graph, with nodes representing entities, relationships representing semantic connections, and attributes describing entity features; the Cypher query language is used to support syndrome inference based on symptom combinations, realize intelligent reasoning of TCM syndrome differentiation, and support dynamic updates of the graph to improve the knowledge system [10].

2.5. Application of the AGBAN model: Knowledge graph embedding and reasoning optimization

2.5.1. Graph attention network architecture

A four-head graph attention network is adopted to assign differentiated importance to neighboring nodes to learn adaptive entity representations. After linear transformation of node features, the transformed features of source and target nodes are concatenated, dotted with the attention vector, activated by LeakyReLU and normalized by Softmax to obtain attention coefficients [11]. The four attention heads focus on four types of relationships: symptom-syndrome, syndrome-TCM treatment, TCM-TCM interaction, and general semantic relevance.

2.5.2. Construction of reinforcement learning diagnostic environment

The TCM diagnosis-treatment process is formalized as a Markov decision process [12]. The state space integrates distributed representations of symptoms and syndromes, path history, and target progress, and the action space is the transfer of adjacent nodes in the graph. A structured reward function is designed, including six components: basic path reward, target achievement reward, graph structure reward, diversity exploration reward, efficiency reward, and cycle penalty, to guide the model to learn the optimal diagnosis-treatment path.

2.5.3. Phased training strategy

A progressive curriculum learning strategy is adopted to train the model in four phases: the first phase is the intensive exploration phase, with 12 steps, the exploration rate ε decreases from 1.0 to 0.8, extensively exploring graph structures and basic diagnostic patterns; the second phase is the balanced learning phase, with 10 steps, the exploration rate decreases to about 0.5, balancing exploration and pattern utilization; the third phase is the strategy optimization phase, with 8 steps, the exploration rate decreases to about 0.3, refining the optimization of diagnosis-treatment strategies; the fourth phase is the refined utilization phase, with 6 steps, the exploration rate decreases to 0.1, optimizing path efficiency and stabilizing diagnostic strategies.

3. Results

3.1. Statistics of knowledge graph construction

Seven types of entities total of 3,089 are extracted from clinical data, and 1,461 relationship edges mainly focusing on clinical associations are constructed. Among them, “symptoms point to syndromes”, “TCM medicines treat syndromes”, and “TCM medicines treat diseases” are the top three relationships; the average degree of the graph is 2.49, with a dense structure, realizing the systematic representation of famous TCM physicians’ diagnosis-treatment knowledge.

3.2. Training results and analysis of the AGBAN model

The TransE model converges well after 200 rounds of training, with the loss stabilizing at 4.5280, the learning rate smoothly decaying from 0.001 to 0.000063, the entity embedding norm maintained at 1.0, and the normalization effect is significant [13].

Principal component analysis visualization shows that drugs and syndromes form a continuous semantic spectrum in the vector space without obvious type boundaries, verifying the TCM principle of "drug-syndrome correspondence"; cluster analysis shows a silhouette coefficient of 0.973 and a CH index of 6,012.21, confirming eight semantic clusters with strong cohesion.

In the AGBAN model test, the diagnosis success rate is 59.19%, and the average reasoning path length is 5 steps, which is 11.6% higher than that of the random strategy. In the link prediction task, the average reciprocal rank of the model is 0.0252, which is 165.4% higher than that of the TransE model; embedding diversity analysis shows that its distribution is more concentrated (0.9173 compared with 1.0001 of TransE), and the ability to capture semantic relationships is better.

3.3. Visualization analysis

3.3.1. Association network between TCM diagnosis and WM use

Through the analysis of co-occurrence relationships between TCM diagnosis and WM entities, this study constructs a clinical knowledge association network combining TCM and WM (**Figure 1**). The analysis results show that one WM may correspond to multiple TCM diagnoses and vice versa. This phenomenon suggests that famous TCM physicians do not simply correspond WMs to specific diseases in clinical practice, but select WMs based on TCM syndrome differentiation results. This syndrome differentiation-based medication model reflects the individualized thinking in integrated TCM-WM diagnosis and treatment, and also provides visual decision support for collaborative TCM-WM treatment in the context of precision medicine.

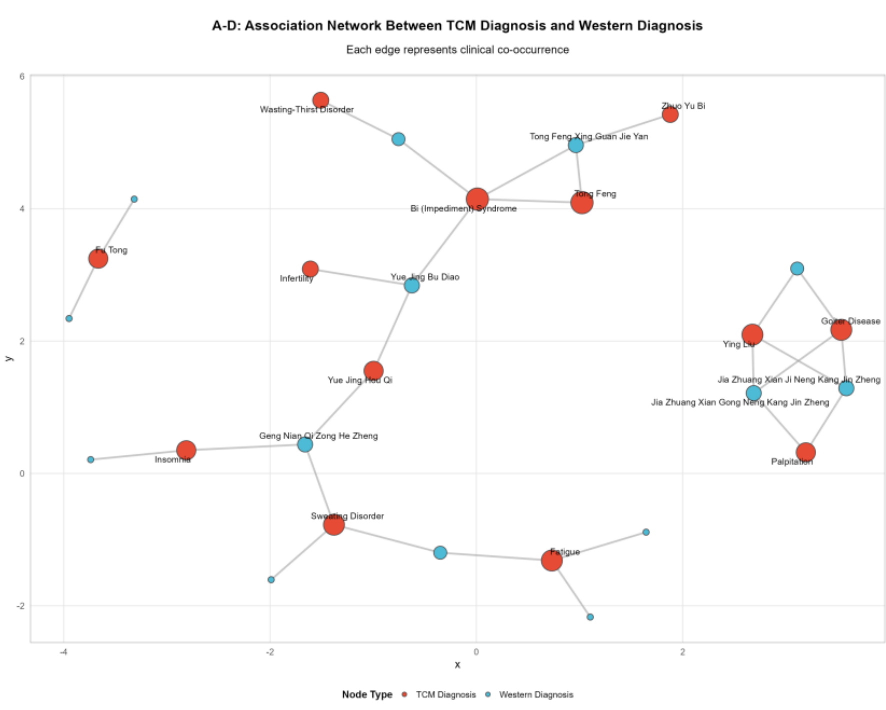

Figure 1. The association network between traditional Chinese medicine diagnosis and the use of Western medicine.

3.3.2. Nodal relationship between TCM diagnosis and patient symptoms

Figure 2 show the network relationship between TCM diagnoses and symptoms. From the network structure, it can be seen that the same TCM diagnosis can correspond to multiple symptom combinations, and different diagnoses may also have common symptoms. This complex network relationship intuitively reflects the core TCM principles of "treating different diseases with the same method" and "treating the same disease with different methods", the key to diagnosis and treatment lies in identifying the core pathogenesis rather than simply addressing symptoms. This network structure helps learners understand the clinical thinking characteristics of famous TCM physicians in "grasping main symptoms and recognizing pathogenesis".

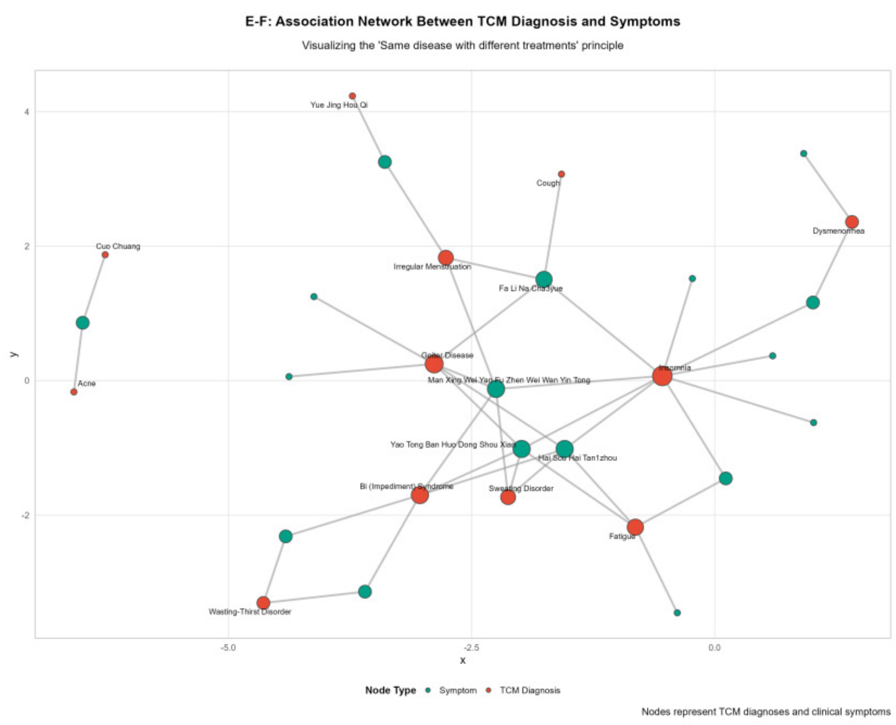

Figure 2. The nodal relationship between traditional Chinese medicine diagnosis and the patient's symptom.

3.3.3. Association network between symptoms and tongue manifestations

Figure 3 also show the association network between symptoms and tongue manifestations [14]. TCM emphasizes "comprehensive four diagnostic methods", and tongue diagnosis, as an important part of inspection, has significant value in syndrome differentiation. From the network analysis, it can be seen that the same symptom may correspond to different tongue manifestation patterns, which may reflect diagnostic differences among different physicians or academic schools; on the other hand, different symptoms may also present the same tongue manifestations, which confirms the diagnostic principle of "tongue diagnosis for root cause", tongue manifestations reflect internal pathogenesis rather than simply corresponding to superficial symptoms. This network provides a basic support for the standardized research of tongue diagnosis and the development of intelligent diagnosis systems.

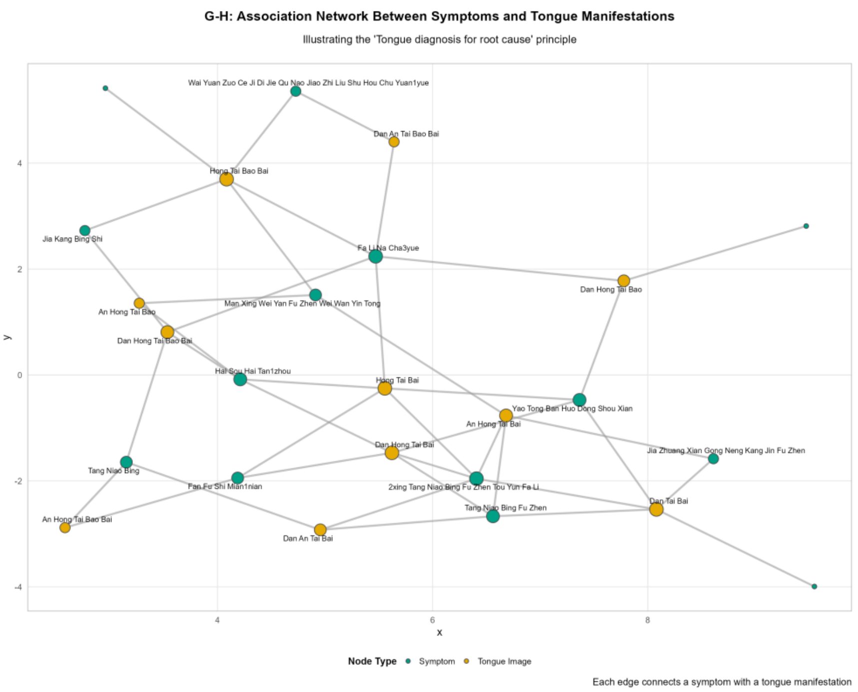

Figure 3. The correlation between symptom nodes and tongue image nodes.

4. Discussion

4.1. Main research results

The large-scale clinical knowledge graph constructed in this study realizes the digital and systematic inheritance of famous TCM physicians' diagnosis-treatment experience. The core results are reflected in three aspects: first, constructing a "digital mirror" of famous TCM physicians' diagnosis and treatment, converting fragmented records into traceable visual decision paths through the "disease-syndrome-symptom-drug" semantic network, and the graph attention network simulates the cognitive focus of physicians, approaching the clinical decision-making process; second, realizing the transformation from "prescription inheritance" to "thinking inheritance", the model learns efficient diagnosis-treatment paths, completing the upgrade from static prescription records to dynamic clinical reasoning simulation, and verifying the drug-syndrome correspondence theory; third, establishing an evolving knowledge inheritance ecosystem, the knowledge graph can be dynamically updated to integrate new clinical data, transforming personal experience into continuously evolving collective wisdom, realizing the "living inheritance" of famous physicians' experience.

4.2. Research limitations and future directions

This study still has certain limitations: first, the current multimodal data fusion mainly focuses on text information, and the in-depth mining of image data such as tongue signs and facial signs is insufficient; second, there are certain inconsistencies in the entity annotation process, which may introduce noise interference; finally, the semantic interference caused by the mixed use of TCM and WM needs to be further addressed.

Future research can be further carried out in the following directions: first, deepen knowledge representation and reasoning mechanisms, explore more advanced embedding models such as RotatE and ComplEx, as well as neuro-symbolic methods integrating logical rules and neural networks; second, strengthen multimodal data fusion, integrate image data such as tongue signs and pulse signs, and construct a more complete diagnostic evidence chain; third, promote the practical application of clinical decision support systems, develop tools such as intelligent question answering, syndrome differentiation assistance, and prescription generation; fourth, use graph mining, causal inference and other methods to extract potential drug pairs, syndrome evolution laws, and prescription combinations from the knowledge graph, promoting the evolution and innovation of TCM theory.

5. Conclusion

Based on more than 3,000 real outpatient medical records of famous TCM physicians, this study constructs a multimodal clinical knowledge graph containing 3,089 entities and 1,461 relationships, systematically representing the clinical diagnosis-treatment experience of famous TCM physicians. The AGBAN model combining graph attention network and reinforcement learning mechanism is introduced to realize adaptive learning and reasoning optimization of diagnosis-treatment paths [15]. The model is significantly superior to traditional methods in diagnosis accuracy, path efficiency, and interpretability.

Through visualization analysis, the complex associations between TCM diagnosis and WM use, TCM diagnosis and symptoms, and symptoms and tongue manifestations are revealed, intuitively presenting the clinical thinking characteristics of famous TCM physicians. This study verifies the feasibility of the multimodal knowledge graph combined with the AGBAN model in TCM academic inheritance and intelligent application, providing new ideas and methods for the digital development of TCM, clinical decision support, and innovation in teacher-apprentice education, and having important practical value for promoting the modern inheritance of TCM.

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Disclosure statement

The authors declare no conflict of interest.

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