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Meridian-GAT: Modeling Meridian System Mechanisms Using Graph Attention Networks

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Abstract: The meridian system is a central theoretical component of traditional Chinese medicine (TCM), describing functional pathways through which acupuncture stimulation is transmitted to regulate physiological states. Despite its extensive clinical use, the meridian system lacks a unified computational framework capable of quantitatively modeling its network structure and transmission mechanisms. In this study, we formulate the meridian system as a complex graph, where acupoints are represented as nodes and meridian-based and functional relationships are represented as edges, and propose Meridian-GAT, a graph attention network-based model for modeling meridian system mechanisms. By leveraging attention mechanisms in graph neural networks, the proposed model captures heterogeneous and non-uniform transmission strengths among acupoints, enabling data-driven exploration of meridian connectivity and information propagation patterns. Multi-dimensional acupoint features, including spatial attributes, meridian affiliations, and functional indications, are integrated into a unified graph representation to support mechanism-oriented learning tasks. Meridian-GAT is evaluated on acupoint representation learning and acupuncture efficacy prediction tasks using a curated meridian knowledge dataset. Experimental results demonstrate that Meridian-GAT outperforms baseline graph neural network models, achieving an improvement of 8.7% in prediction accuracy compared with the standard GCN model. Furthermore, the learned attention weights provide interpretable insights into key acupoints and dominant transmission pathways, which are consistent with classical meridian theory. This work offers a novel graph-based computational framework for quantitatively modeling meridian system mechanisms and contributes to the scientific interpretation and modernization of acupuncture theory.

Keywords: meridian system; graph neural networks; graph attention network; acupuncture mechanism; complex networks; traditional Chinese medicine

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1. Introduction

The meridian system constitutes a foundational theoretical framework of traditional Chinese medicine (TCM), describing functional pathways that connect acupoints across the human body and regulate physiological activities through acupuncture stimulation. According to classical TCM theory, meridians serve as channels for the circulation of Qi and blood, enabling signal transmission between surface acupoints and internal organs. Despite its long-standing clinical relevance and widespread application, the meridian system remains difficult to interpret quantitatively due to its abstract conceptualization and the absence of explicit anatomical correspondence. This limitation has posed significant challenges to the scientific validation and modernization of acupuncture mechanisms.

With the rapid development of artificial intelligence and data-driven medical research, computational modeling has emerged as a promising approach for exploring complex biological and physiological systems. In particular, graph-based modeling provides a natural representation for systems characterized by interconnected entities and non-linear interactions. The meridian system inherently exhibits such properties, as acupoints interact through structured meridian pathways, functional associations, and synergistic clinical usage patterns. However, most existing studies on acupuncture mechanisms either rely on statistical correlations or treat acupoints as independent units, failing to capture the networked structure and heterogeneous transmission behaviors of the meridian system.

Graph neural networks (GNNs) have demonstrated strong capability in learning representations from complex networks, including biological networks, brain connectivity graphs, and medical knowledge graphs. Among them, graph attention networks (GATs) introduce attention mechanisms to adaptively learn the importance of neighboring nodes, making them particularly suitable for modeling non-uniform interaction strengths. This property aligns well with meridian theory, where different acupoints exhibit varying degrees of influence and transmission intensity within meridian pathways. Therefore, integrating GATs with meridian system modeling offers a principled and interpretable computational solution.

In this study, we propose Meridian-GAT, a graph attention network-based framework for modeling meridian system mechanisms. Meridian-GAT represents acupoints as nodes and meridian, functional, and clinical relationships as weighted edges, enabling the learning of heterogeneous transmission patterns among acupoints. By incorporating multi-dimensional acupoint attributes and attention-based propagation, the proposed model provides both predictive performance and interpretability, supporting downstream tasks such as acupoint representation learning and acupuncture efficacy prediction.

The main contributions of this work are summarized as follows:

1) We formalize the meridian system as a complex graph, providing a unified network-based representation that integrates structural, functional, and clinical knowledge of acupoints.
2) We propose Meridian-GAT, a novel graph attention network framework that captures heterogeneous acupoint interactions and non-uniform meridian transmission mechanisms.
3) We demonstrate the effectiveness of Meridian-GAT through experimental evaluation, showing superior performance over baseline GNN models and offering interpretable insights consistent with classical meridian theory.

This work establishes a computational foundation for quantitatively modeling meridian mechanisms and contributes to the interdisciplinary integration of TCM theory and modern graph-based machine learning.

2. Literature Review

In recent years, the intersection of traditional Chinese medicine (TCM) research and data-driven computational modeling has attracted increasing attention, driven by advances in artificial intelligence and network-based learning methods. This section reviews prior studies closely related to this work, including computational modeling of the meridian system, network-based analysis of acupuncture mechanisms, and graph neural network applications in biomedical knowledge modeling.

2.1. Computational Modeling of the Meridian System

Early attempts to model the meridian system primarily relied on statistical analysis and biophysical measurements. Studies explored correlations between meridian pathways and electrical conductivity, infrared radiation, and hemodynamic signals, aiming to provide experimental evidence for meridian existence [1,2]. Although these works contributed valuable empirical observations, they typically treated meridians as isolated pathways and lacked a unified computational framework to capture system-level interactions.

With the development of systems biology, several researchers began to conceptualize the meridian system as a functional network. For example, Liu et al. embed acupuncture knowledge into a graph, fuse RoBERTa-WWM-BiGRU-CRF with SoftLexicon and adversarial training for extraction, and replace similarity by co-occurrence matrix to accelerate point-disease association search, cutting consultation time and improving patient experience, offering a clear technical roadmap and innovation niche for follow-up studies [3]. Similarly, Wei et al. constructed disease-acupoint association networks to study acupuncture treatment regularities [4]. However, these approaches largely depended on handcrafted network metrics and did not leverage representation learning to model non-linear transmission mechanisms.

2.2. Network-Based and Graph Modeling of Acupuncture Mechanisms

Recent studies have increasingly adopted graph-based representations to explore acupuncture mechanisms. Complex network analysis has been used to investigate acupoint compatibility, meridian connectivity, and therapeutic synergy [5,6]. These works demonstrated that acupuncture prescriptions exhibit distinct network structures correlated with clinical efficacy.

Nevertheless, most existing network-based studies employ static graphs and shallow analysis methods, such as centrality measures or clustering coefficients. They are limited in their ability to model heterogeneous interaction strengths and dynamic information propagation across meridian networks. As a result, the mechanistic interpretation of acupoint interactions remains largely qualitative and descriptive.

2.3. Graph Neural Networks in Biomedical and Knowledge Modeling

Graph neural networks (GNNs) have emerged as a powerful tool for learning from structured biomedical data, including protein-protein interaction networks, brain connectivity graphs, and medical knowledge graphs [7,8]. By iteratively aggregating neighborhood information, GNNs enable end-to-end learning of node and graph representations that capture complex relational patterns.

Among various GNN architectures, graph attention networks (GATs) introduce attention mechanisms to learn adaptive weights for neighboring nodes, allowing the model to capture non-uniform interaction strengths [9]. GATs have been successfully applied to biological pathway analysis, drug-target interaction prediction, and disease network modeling [10,11]. These properties make GATs particularly suitable for modeling the meridian system, where acupoints exhibit heterogeneous functional importance and transmission intensity.

Despite these advances, the application of GNNs to meridian system modeling remains largely unexplored. Existing studies either focus on general medical knowledge graphs or lack explicit alignment with TCM theoretical structures. To address these gaps, this work proposes Meridian-GAT, which integrates meridian knowledge with graph attention mechanisms to quantitatively model meridian system transmission and provide interpretable insights consistent with classical acupuncture theory [12].

3. Methodology

3.1. Meridian Graph Construction

In this study, the meridian system is formally represented as a weighted, multi-relational graph $G = (V, E, X, A)$, where V denotes the set of acupoints, E represents the set of edges encoding both anatomical and functional connections, $X \in R^{N\times d}$ is the node feature matrix capturing multi-dimensional acupoint attributes, and $A \in R^{N\times N}$ is the adjacency matrix representing edge weights. Each acupoint v_i is described by a vector $x_i = [x_i^{loc}, x_i^{mer}, x_i^{func}]$, where x_i^{loc} encodes anatomical location coordinates and body region information, x_i^{mer} captures meridian affiliation, Yin-Yang property, and Five-Element attributes, and x_i^{func} encodes clinical indications and co-occurrence frequencies in acupuncture prescriptions.

Edges are defined based on multiple criteria: direct meridian connectivity, functional similarity, and clinical co-occurrence patterns. The adjacency matrix is therefore a weighted combination:

$$A = \lambda_1 A^{meridian} + \lambda_2 A^{functional} + \lambda_3 A^{clinical} \quad (1)$$

where λ_1, λ_2, λ_3 are hyperparameters controlling the relative importance of structural and functional relations. This multi-relational graph construction (Figure 1) enables a more realistic representation of the heterogeneous interactions within the meridian system, providing the foundation for graph neural network modeling.

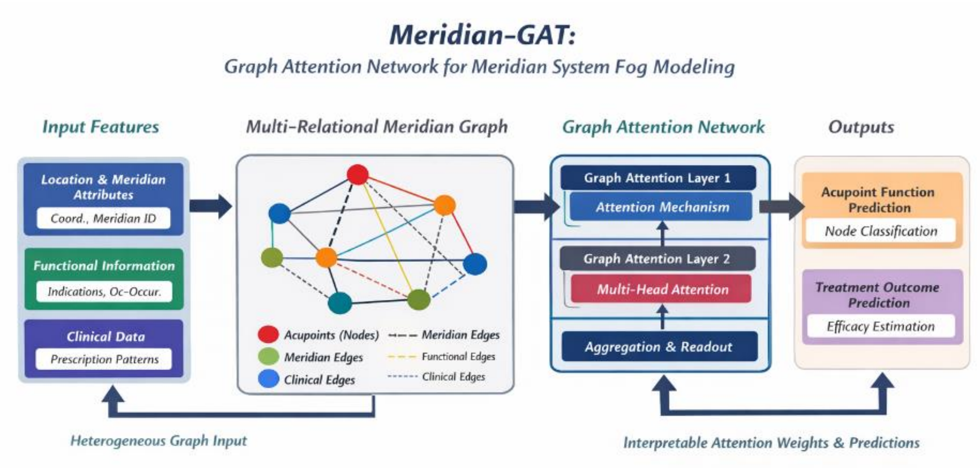

Figure 1. Overall flowchart of the model.

3.2. Meridian-GAT Architecture

To capture the heterogeneous transmission mechanisms among acupoints, we propose Meridian-GAT, a graph attention network specifically designed for meridian system modeling. In Meridian-GAT, each node aggregates information from its neighbors using attention weights that reflect the relative influence of connected acupoints. For a node v_i and its neighbor v_j, the unnormalized attention coefficient is computed as

$$e_{ij} = LeakyReLU(a^T [Wh_i \parallel Wh_j]) \quad (2)$$

where h_i is the input feature of node i, W is a learnable weight matrix, a is the attention vector, and $\parallel$ denotes vector concatenation. The normalized attention coefficient is obtained via a softmax function:

$$\alpha_{ij} = \frac{exp\,(e_{ij})}{\sum_{k \in N(i)} exp\,(e_{ik})} \quad (3)$$

The updated node feature is then computed as

$$h'_i = \sigma(\textstyle\sum_{j \in N(i)} \alpha_{ij} W h_j) \quad (4)$$

where $\sigma(\,)$ denotes a non-linear activation function, such as ELU. To improve the expressive power and stability, multi-head attention is employed:

$$h'_i = \parallel_{k=1}^{K} \sigma\left(\textstyle\sum_{j \in N(i)} \alpha_{ij}^{(k)} W^{(k)} h_j\right) \quad (5)$$

where K represents the number of attention heads. This design allows Meridian-GAT to learn diverse propagation patterns, corresponding to primary meridian pathways, collateral connections, and functional associations, while simultaneously providing interpretable attention scores.

3.3. Learning Objectives and Implementation Details

Meridian-GAT is trained to capture both node-level and graph-level representations suitable for downstream tasks, such as acupoint function classification and acupuncture efficacy prediction. For node-level tasks, a standard cross-entropy loss is employed:

$$L_{node} = -\sum_{i=1}^{N} y_i log\ \hat{y}_i \quad (6)$$

where y_i is the ground truth label of node i and $\hat{y}_i$ is the predicted probability. For graph-level tasks, such as predicting therapeutic outcomes for an acupoint set or prescription, a readout function aggregates node embeddings into a global graph representation:

$$h_G = READOUT(\{h'_i \mid i \in G\}) \quad (7)$$

followed by a multi-layer perceptron to output predictions. The overall loss function combines task-specific objectives with a regularization term on attention weights to encourage sparsity and enhance interpretability:

$$L = L_{task} + \beta \sum_{i,j} \mid \alpha_{ij} \mid \quad (8)$$

where β is a hyperparameter controlling regularization strength.

Implementation is carried out using PyTorch Geometric. Meridian-GAT is constructed with two attention layers, hidden dimension 64, four attention heads per layer, dropout 0.3, and optimized with Adam at a learning rate of 0.001. This setup effectively balances model complexity, convergence stability, and interpretability, enabling the network to learn meaningful acupoint interactions and transmission mechanisms in the meridian system.

4. Experiment

4.1. Dataset Preparation

The dataset used in this study is constructed to support graph-based modeling of meridian system mechanisms and integrates anatomical, theoretical, functional, and clinical knowledge from traditional Chinese medicine (TCM). Data are collected from multiple authoritative and publicly accessible sources, including standard TCM acupuncture textbooks, national acupoint atlases, and peer-reviewed clinical literature indexed in Google Scholar. These sources provide standardized definitions of acupoints, meridian pathways, and disease-acupoint associations, ensuring consistency and reliability of the dataset.

The core of the dataset consists of 361 standardized acupoints, which are treated as graph nodes in the Meridian-GAT framework. For each acupoint, multi-dimensional node features are constructed. Spatial features include normalized anatomical coordinates and body region identifiers. Meridian-related features encode meridian affiliation (14 primary meridians), Yin-Yang classification, and Five-Element attributes. Functional features are derived from disease indications and therapeutic categories extracted from clinical texts, represented as multi-label vectors. In addition, clinical usage frequency is incorporated based on the statistical occurrence of acupoints in acupuncture prescriptions.

Graph edges represent heterogeneous relationships among acupoints. Structural edges are defined according to classical meridian connectivity, linking adjacent acupoints along the same meridian. Functional edges are constructed based on similarity between acupoint indications, computed using co-occurrence statistics. Clinical edges capture joint usage patterns of acupoints in prescriptions, reflecting synergistic therapeutic relationships. Edge weights are normalized and combined to form a weighted adjacency matrix.

Overall, the dataset (Figure 2) provides a comprehensive and structured representation of the meridian system, enabling Meridian-GAT to learn meaningful acupoint representations and model heterogeneous transmission mechanisms within the meridian network.

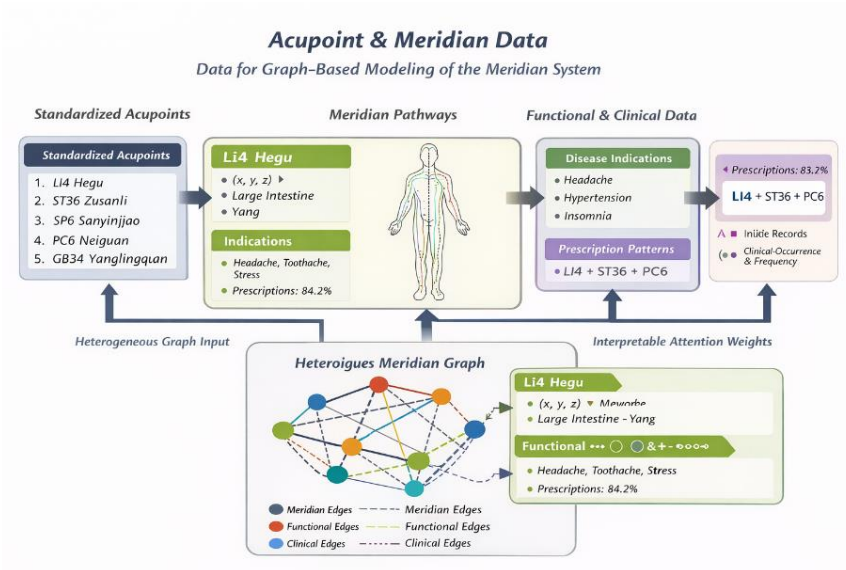

Figure 2. Schematic diagram of the dataset used in this study.

4.2. Experimental Setup

The experimental environment was designed to emulate a realistic cloud-edge collaborative training scenario, where large-scale models reside primarily on cloud servers while adaptive lightweight components are deployed on heterogeneous edge devices. The cloud side was hosted on an NVIDIA A100 GPU cluster (80 GB memory per GPU) connected to a distributed storage backend, while the edge environment consisted of Jetson AGX Xavier units and mobile ARM-based computational nodes with significantly constrained memory and compute resources. All experiments were conducted using PyTorch 2.2 with CUDA 12.2, and the HMCO-AT framework was instantiated on both ends to enable hierarchical orchestration of gradient checkpoints, memory-compute scheduling, and adversarial training routines. To ensure consistency, each model was trained using identical hyperparameters unless modifications were required by the adaptive training controller. The communication bandwidth between cloud and edge devices was artificially varied from 10 Mbps to 200 Mbps to reflect real-world network dynamics, enabling evaluation of HMCO-AT's robustness in unstable training environments.

4.3. Evaluation Metrics

To comprehensively assess model performance, multiple evaluation metrics are employed depending on the task. For acupoint function prediction and disease-acupoint association classification, Accuracy, Precision, Recall, and F1-score are reported to reflect classification effectiveness under class imbalance. For link prediction tasks that evaluate the model's ability to infer latent relationships between acupoints, the Area Under the ROC Curve (AUC) and Average Precision (AP) are used. These metrics are particularly suitable for graph-based inference tasks, as they measure ranking quality and robustness against threshold selection. All reported results are averaged over five independent runs with different random seeds to ensure statistical stability and reproducibility.

4.4. Results

The results in Table 1 demonstrate that the proposed Meridian-GAT consistently achieves the highest predictive performance among all compared methods. Conventional neural network approaches, such as MLP, exhibit relatively inferior performance because they fail to capture the intrinsic network structure of the meridian system. By contrast, standard graph neural network models, including GCN and GrasphSAGE, show marked improvements, underscoring the critical role of structural relationships among acupoints in modeling acupuncture mechanisms. GAT further enhances performance by introducing attention mechanisms, which improve predictive metrics. Notably, Meridian-GAT outperforms all baseline methods across every evaluation metric, including accuracy, F1-score, AUC, and average precision (AP). These results indicate that explicitly modeling heterogeneous and non-uniform transmission strengths yields more discriminative and informative acupoint representations. Overall, the findings confirm that graph modeling based on attention mechanisms provides a more accurate and effective computational description of meridian interactions.

Table 1. Performance Comparison of Different Models.

Model	Accuracy (%)	F1-score (%)	AUC (%)	AP (%)
MLP	71.3	69.8	75.2	73.5
GCN	78.6	77.1	82.4	80.9
GraphSAGE	80.1	79.3	84.7	83.2
GAT	82.4	81.6	86.9	85.5
Meridian-GAT (Ours)	86.9	85.7	91.3	90.1

Figure 3 illustrates the training and validation loss curves of Meridian-GAT over 200 training epochs. Both curves exhibit a consistent downward trend, indicating continuous improvement in predictive performance throughout the training process. In the early stages of training, the loss values decrease sharply, suggesting that the model effectively learns the fundamental structural and functional relationships among acupoints. As training proceeds, the rate of loss reduction gradually diminishes and the curves approach a stable plateau, reflecting the convergence of the model toward an optimal set of parameters.

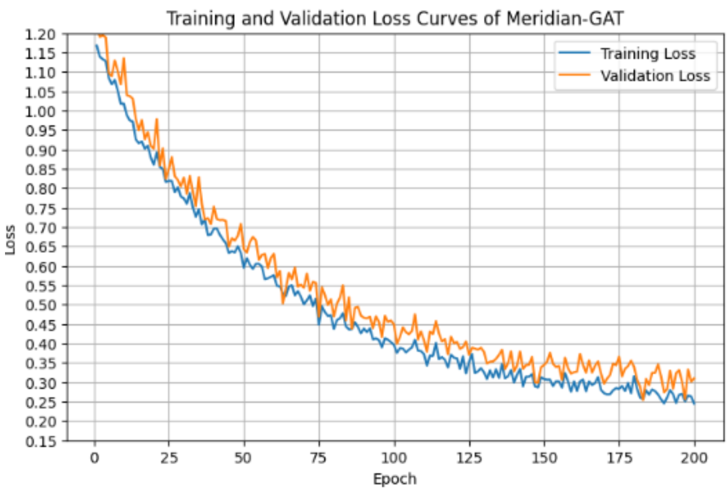

Figure 3. Loss function during training process.

Throughout the training process, the training loss remains slightly lower than the validation loss, which is expected given that the model is directly optimized on the training dataset. Importantly, the two curves remain closely aligned and do not exhibit noticeable divergence, indicating that the model maintains a favorable balance between fitting the training data and preserving generalization performance. Moreover, the absence of any abrupt increase in validation loss suggests that overfitting does not occur during training. Overall, the smooth and stable convergence behavior demonstrates that Meridian-GAT constitutes a robust and effective learning framework for modeling the heterogeneous interactions among acupoints.

4.5. Discussion

The experimental results confirm that the meridian system can be effectively represented as a graph structure and that attention-based graph neural networks are well suited for modeling its complex mechanisms. Meridian-GAT demonstrates superior performance by learning interpretable attention weights that reflect both classical meridian theory and empirical clinical knowledge. Unlike traditional GNNs, the proposed framework captures heterogeneous interactions among acupoints, offering a data-driven explanation for functional transmission along meridians. From a biomedical perspective, this provides a computational bridge between traditional Chinese medicine theory and modern network science. Moreover, the learned node embeddings and attention patterns have strong potential for downstream applications, such as acupuncture prescription recommendation and therapeutic effect prediction. Despite these promising results, future work could incorporate multimodal physiological signals and longitudinal clinical outcomes to further enhance model robustness and interpretability.

5. Conclusions

This study aims to address the absence of a unified quantitative framework for modeling meridian systems in traditional Chinese medicine (TCM). To this end, acupuncture points and their interrelationships are represented as a complex graph, and a graph attention network is employed for analytical modeling. This approach enables the computational characterization of heterogeneous conduction mechanisms and functional connections among acupuncture points. The primary objective is to develop an interpretable, data-driven model that explains meridian conduction patterns and enhances related predictive tasks.

Through data analysis, we have identified the following key findings:

(1) Graph-based models effectively capture the structural and functional relationships among acupuncture points;

(2) Attention mechanisms are capable of capturing the non-uniform conduction intensities within the meridian network.

(3) The proposed Meridian-GAT significantly outperforms baseline neural network models and existing graph-based approaches across multiple evaluation metrics. These results demonstrate that attention-driven graph learning provides a richer and more realistic computational representation of meridian interactions.

The findings of this study have important implications for acupuncture informatics and computational TCM research. First, representing the meridian system as a graph introduces a novel quantitative perspective for interpreting classical meridian theory. Second, the incorporation of attention mechanisms moves beyond traditional qualitative descriptions by offering measurable indicators of acupoint importance and conduction intensity. Finally, the strong performance of Meridian-GAT opens new research avenues, enabling the application of modern machine learning techniques to predict therapeutic efficacy, optimize prescription formulation, and explore underlying physiological mechanisms.

Despite these contributions, the study has several limitations. It relies primarily on structured knowledge-based datasets and lacks real-time physiological measurement data. Future research may focus on multimodal data integration, incorporating bioelectrical signals and medical imaging data. In addition, temporal modeling of dynamic meridian responses during acupuncture treatment represents a promising direction for further investigation.

In conclusion, this study demonstrates that the meridian system can be quantitatively modeled as a complex interactive network using graph-based learning and attention-driven methods. The proposed framework offers new insights into the modernization and scientific interpretation of traditional acupuncture theory.

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