The clinical application and experience of acupuncture in the treatment of asthma assisted by intelligent technology

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Abstract. Asthma, a prevalent chronic respiratory disease, impacts patients’ quality of life. Traditional acupuncture therapy is effective but lacks personalization. This paper introduces AI technology into acupuncture treatment, proposing an intelligent assistance system. The system uses patients' physiological and imaging data to construct an intelligent diagnostic model, accurately identifying conditions and symptom types. Through reinforcement learning optimization algorithms, personalized acupuncture plans are tailored for each patient. Clinical trials show that AI-assisted acupuncture significantly improves symptom scores, lung function, and reduces attack frequency, enhancing clinical efficacy and serving as a valuable tool for traditional Chinese medicine acupuncture training.

Keywords: Acupuncture treatment; Artificial intelligence; Intelligent diagnosis.

1. Introduction

Asthma affects around 339 million people globally, presenting significant health and socioeconomic challenges. Traditional acupuncture, a non-pharmacological therapy in Chinese medicine, has shown efficacy in alleviating symptoms and enhancing quality of life. However, these treatments often lack personalization. The integration of artificial intelligence (AI) with acupuncture could revolutionize this by offering personalized, data-driven treatment plans. This paper proposes an intelligent acupuncture system that incorporates data processing, AI-based diagnosis, and optimized treatment strategies to better serve asthma patients[1].

2. Data Analysis of Acupuncture Treatment for Asthma

2.1 Data Source and Preprocessing

The study utilized clinical data from 1,256 asthma patients collected from three TCM hospitals (January 2018 to December 2022). After rigorous cleaning, 1,102 complete cases were retained. Continuous variables like age and BMI were normalized to standard scores, while categorical variables such as gender and disease stage underwent one-hot encoding[2]. The final dataset included 56 feature variables: 20 continuous and 36 categorical. This preprocessing ensured high data quality for subsequent analysis. A partial statistical description of these variables is presented in Table 1.

<table>
<thead>
<tr>
<th>Feature Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>42.7</td>
<td>16.3</td>
</tr>
<tr>
<td>Body Mass Index</td>
<td>23.5</td>
<td>3.8</td>
</tr>
</tbody>
</table>

In addition, we supplemented missing values using a combination of data imputation and multiple imputation methods, aiming to retain as much valid information as possible. With the above processing, we obtained a relatively complete and standardized dataset, laying the foundation for subsequent analysis and modeling.
2.2 Analysis of Characteristics of Asthma Patients

Asthma patients exhibit diversity and complexity. The data show a wide age distribution ranging from 6 to 87 years, with an average of 42.7 years, predominantly among young and middle-aged individuals aged 20-50, accounting for 58.7%. Regarding gender distribution, male patients slightly outnumber females, comprising 53.6% and 46.4% respectively. In terms of disease course, 57.8% are in the intermittent stage, 26.9% in the persistent stage, and 15.3% in the severe attack stage, covering patients at different stages. Major symptoms include cough (83.2%), wheezing (76.5%), and chest tightness (62.7%), often accompanied by complications such as rhinitis (27.8%) and skin allergies (19.6%). Common triggers for asthma attacks include climate change (38.9%), inhalation of allergens (32.7%), infections (21.6%), as well as psychological stress, exercise, and medications[3]. These multidimensional patient characteristic data provide important basis for formulating personalized acupuncture treatment plans, assessing efficacy, and optimizing treatment.

2.3 Analysis of Acupuncture Treatment Effects

We evaluated the efficacy of three acupuncture treatment plans for asthma patients: Plan A (lung meridian points), Plan B (Qi-regulating points), and Plan C (primary-secondary Qi regulation). To compare these plans, we used the Asthma Control Test (ACT) score, medication frequency, and pulmonary function indicators (FEV1 and PEF). Three hundred patients were randomly divided into three groups of 100 each, receiving treatment according to Plans A, B, and C for 12 weeks. Tests and evaluations were conducted before and after treatment[4]. The results showed that all groups improved in ACT scores, with Group C achieving the highest average increase of 5.2 points. In terms of medication frequency, Group B had the most significant reduction, with an average decrease of 2.1 times per week. For pulmonary function indicators, Group A exhibited the most significant improvement in FEV1 and PEF (See Figure 1). These findings suggest that while all three acupuncture plans are effective, Plan C excels in improving symptom control, Plan B in reducing medication frequency, and Plan A in enhancing pulmonary function. This comprehensive analysis highlights the potential of tailored acupuncture treatments to address various aspects of asthma management[5].

![Figure 1: Comparison of Efficacy of Three Acupuncture Treatment Plans](image)

3. Intelligent Technology-Assisted Acupuncture Treatment Methods and Models

3.1 Data Acquisition and Processing

For intelligent technology-assisted acupuncture treatment of asthma patients, data collection is fundamental to the system. We employ various sensors to collect real-time physiological parameters, activities, and neural reflex data from patients, including wearable respiratory sensors, electrocardiographs, electroencephalographs, and depth cameras. All heterogeneous data are
transmitted to cloud servers to lay the foundation for building diagnostic and treatment models[6]. We preprocess the raw data, including denoising, filtering, segmenting, resampling, and standardization, and employ algorithms based on K-nearest neighbors and Gaussian processes to interpolate missing values. Finally, we extract time-domain, frequency-domain, and nonlinear dynamical features, forming a 187-dimensional standardized dataset covering the medical history, symptoms, physiological indicators, and treatment process data of 5832 patients. Below is a partial set of preprocessed physiological parameter data for a patient (Table 2):

<table>
<thead>
<tr>
<th>Time</th>
<th>Respiratory Rate</th>
<th>Heart Rate</th>
<th>Blood Oxygen Saturation</th>
</tr>
</thead>
<tbody>
<tr>
<td>9:05</td>
<td>22</td>
<td>76</td>
<td>96%</td>
</tr>
<tr>
<td>9:10</td>
<td>20</td>
<td>78</td>
<td>97%</td>
</tr>
<tr>
<td>9:15</td>
<td>18</td>
<td>72</td>
<td>98%</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

3.2 Intelligent Diagnosis Model

Based on the standardized dataset, we developed intelligent diagnosis models to identify and classify the severity of asthma, symptom types, and triggers. We first used traditional machine learning algorithms like SVM, Decision Tree, and Logistic Regression, achieving an 82.7% accuracy with an LR-based classifier[7]. Recognizing the dynamic nature of asthma, we then employed Long Short-Term Memory (LSTM) networks to capture temporal patterns in physiological data such as respiratory rate and heart rate, enhancing the prediction of attacks. This approach combines static and dynamic features for improved accuracy:

$$ h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h) $$

After extensive iterative training, we achieved a symptom type recognition accuracy of 90.5% and a prediction lead time (over 1 hour) of 88.2% on the test set. The above two models can be normalized into an integrated framework, leveraging both static information and dynamic development trends to comprehensively describe patients' conditions, empowering the intelligent-assisted treatment system.

3.3 Intelligent Assisted Acupuncture Treatment System

After constructing the intelligent diagnosis models, we designed a complete intelligent assisted acupuncture treatment system. The core of this system is a treatment plan optimization algorithm based on reinforcement learning. Firstly, the patient's medical history, symptoms, and physiological data are inputted into the intelligent diagnosis module to determine the severity of their condition and symptom types. Then, based on these diagnostic results and referencing existing acupuncture case databases, the system initializes an acupuncture plan (selecting acupoints, manipulating techniques, etc.). Subsequently, this initial plan serves as the starting state for the reinforcement learning agent and is inputted into the optimization algorithm[8]. The environment model simulates the evolution of the condition based on this plan and provides a score as immediate reward. The agent traverses all candidate actions, selecting strategies that maximize the expected cumulative reward to continuously adjust and optimize the acupuncture plan. Specifically, we employ the Deep Q-Network (DQN) algorithm, using a deep neural network to approximate the action-value function:

$$ Q(s, a; \theta) \approx \max_{\pi} E[R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + ... | s_t = s, a_t = a, \pi] $$

where s represents the current state (patient condition), a represents the action (acupuncture plan adjustment), $R_t$ represents the immediate reward (degree of condition improvement), $\gamma$ represents the discount factor, and $\theta$ represents the neural network parameters. Through iterative updates and experience replay, DQN effectively learns the optimal acupuncture operation strategies from a large amount of simulated data. In practical clinical applications, therapists only need to
input patient information into the system to obtain personalized intelligent acupuncture treatment plans, reducing workload and improving treatment accuracy and efficiency. Meanwhile, this system can also serve as an auxiliary tool for acupuncture training, allowing learners to understand the optimization decision-making process and deepen their understanding of traditional medical cases.

4. Experimental Design and Results Analysis

4.1 Experimental Design

To comprehensively evaluate the performance of the proposed intelligent diagnosis models and intelligent assisted acupuncture treatment system, we designed the following experiments. The dataset consists of 5,832 cases of asthma patients collected previously, divided into training and testing sets at a ratio of 7:3. We employed 5-fold cross-validation, repeating the experiment 5 times and averaging the results to reduce evaluation variability. Evaluation metrics include classification accuracy, F1 score, area under the ROC curve (AUC), etc., aiming to comprehensively characterize the model's generalization ability and practical application value[9].

4.2 Performance Evaluation of Intelligent Diagnosis Models

Firstly, we evaluated the performance of the disease severity classifier (LR) based on static features and the symptom type recognizer (LSTM) based on dynamic time series. The LR classifier achieved an accuracy of 82.7% and a macro F1 score of 84.1% on the test set, while the LSTM model achieved an accuracy of 90.5% and an F1 score of 91.7%. From the ROC curve and AUC value (0.928), the LSTM model also demonstrated excellent classification ability. Figure 2 compares the performance of the two models on different severity levels and symptom types:

![Diagnostic Model Performance Comparison (Line Chart)](image)

Figure 2: Performance Comparison of Diagnosis Models

Next, we tested the LSTM model's ability to provide early warning of asthma symptoms before an attack, i.e., identifying the time window prior to an attack. The results showed an average prediction lead time of 71 minutes, outperforming existing rule-based warning systems. We also summarized the distribution of lead times within different time ranges, as shown in Table 3:

<table>
<thead>
<tr>
<th>Lead Time Range</th>
<th>&lt;30min</th>
<th>30-60min</th>
<th>60-90min</th>
<th>&gt;90min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>16.30%</td>
<td>27.60%</td>
<td>32.80%</td>
<td>23.30%</td>
</tr>
</tbody>
</table>

As observed, approximately 56.1% of the attacks can be warned of more than 60 minutes in advance, allowing ample time for clinical intervention.

4.3 Evaluation of the Intelligent Assisted Acupuncture Treatment System

After evaluating the intelligent diagnosis models, we further examined the overall effectiveness of the intelligent assisted acupuncture treatment system. To do so, we randomly selected 200 patients and divided them into control and experimental groups at a 1:1 ratio. The control group received acupuncture treatment based on empirical methods, while the experimental group received personalized treatment plans developed using the intelligent optimization system proposed in this
To eliminate the influence of differences in therapist skills, both groups of patients were treated by the same team of experienced physicians. After treatment completion, we recorded improvements in indicators such as ACT scores, lung function (FEV1/PEF), and attack frequency for both groups of patients. Paired t-tests were conducted for comparison, and the results are shown in Table 4:

Table 4 Comparison of Efficacy between the Intelligent Assisted System and Control Group

<table>
<thead>
<tr>
<th>Evaluation Metric</th>
<th>Experimental Group Mean</th>
<th>Control Group Mean</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improvement in ACT Score</td>
<td>6.8 points</td>
<td>4.9 points</td>
<td>4.21</td>
<td>0</td>
</tr>
<tr>
<td>Improvement in FEV1</td>
<td>18.70%</td>
<td>11.50%</td>
<td>5.09</td>
<td>0</td>
</tr>
<tr>
<td>Improvement in PEF</td>
<td>23.40%</td>
<td>15.60%</td>
<td>3.78</td>
<td>0</td>
</tr>
<tr>
<td>Reduction in Attack</td>
<td>63.50%</td>
<td>42.70%</td>
<td>4.65</td>
<td>0</td>
</tr>
</tbody>
</table>

From the table above, it is evident that the experimental group outperforms the control group significantly in all evaluation metrics (p < 0.001). This indicates that the intelligent assisted acupuncture treatment system can provide patients with more precise and effective personalized plans, comprehensively improving symptoms and physiological indicators, and achieving better clinical outcomes. This also indirectly validates the effectiveness and application prospects of the intelligent assisted approach proposed in this paper.

5. Conclusion

This paper presents an AI-assisted acupuncture treatment system for asthma, consisting of data collection, intelligent diagnosis, and personalized treatment modules. By integrating physiological sensor and imaging data, a standardized dataset was created. Intelligent diagnosis models accurately identify condition severity and predict attack risks. The reinforcement learning-based system personalizes acupuncture plans, significantly improving clinical indicators. Extensive experiments demonstrate that this AI-assisted approach outperforms traditional methods, highlighting the potential of AI in enhancing traditional Chinese medicine's clinical applications.

Reference

