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Prediction of Budd-Chiari syndrome based on attention mechanisms of high-risk factors in multi-hop graph learning

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Budd-Chiari syndrome (BCS) is a series of clinical syndromes caused by obstruction of the hepatic vein and/or hepatic segment inferior vena cava, which can seriously damage the health of the body and lead to patient death [1]. Over recent years, with the improvement of diagnostic technology, especially the introduction of multidisciplinary intervention methods, more and more potential cases have been discovered and treated [2]. However, conventional clinical diagnosis is usually based on traditional indicators [3], and diagnostic criteria are largely dependent on the results of statistical analyses, often ignoring the importance of the association between different factors [4], especially high-risk factors, and the disease [5]. Effectively capturing the critical factors that contribute to disease occurrence is the challenge for improving the predictive performance of BCS.

To address the aforementioned issues, we propose the method ARM-BCS (attentional multi-hop graph learning model-BCS) based on the attentional mechanisms of high-risk factors in a multi-hop graph learning framework to predict BCS. Significantly, ARM-BCS utilizes attentional mechanisms to capture crucial factors affecting BCS recurrence and to dig deeper into the hidden associations between each factor and the disease. ARM-BCS simultaneously focuses on the associations between different factors, using attentional diffusion to incorporate multi-hop contextual information into each layer of the graph neural network computation, and aggregating factors with hidden associations through the depth of layer normalization, thus enabling the augmentation of the sample data to predict the potential BCS more effectively.

The primary contributions of this study are summarized below. (1) We model BCS data using a novel graph learning approach. Our approach aims to more effectively predict potential BCS by taking into account the influence of different factors, especially high-risk factors, on the occurrence of BCS. (2) We introduce a multi-hop attention mechanism designed to capture and exploit the deep neighbourhood associations present in the sample data. (3) We conducted extensive experiments on real-world data based on BCS consensus guideline diagnostic criteria to demonstrate the effectiveness of ARM-BCS in predicting potential BCS and understanding the mechanisms of risk factors. The framework of ARM-BCS is shown in Figure 1.

Data collection and organization. The data used in this study were obtained from 754 BCS patients who received interventional treatment at The Affiliated Hospital of Xuzhou Medical University from January 2015 to June 2022, and were approved by the Ethics Committee. Screening criteria for clinical data were based on the 2021 Asia-Pacific Association for the Study of Liver (APASL) consensus guidelines and confirmed by angiography, computed tomography and color Doppler ultrasound, resulting in 243 positive samples and 511 negative samples. For more detailed information about the datasets, please refer to Appendix A.

ARM-BCS algorithm. We propose an attentional multi-hop graph learning framework (ARM-BCS) to predict BCS. ARM-BCS models BCS data using graph neural networks and captures deep neighborhood associations between pathogenic factors through attention based multi-hop mechanisms [6]. Additionally, ARM-BCS incorporates multiple features to improve the predictive accuracy of the model [7]. Please refer to Appendix B for details of the ARM-BCS al-

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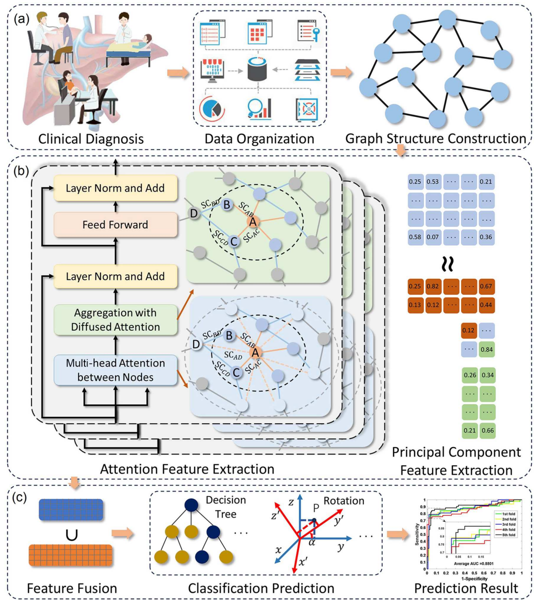

Figure 1 (Color online) Framework of ARM-BCS model. (a) Data organization; (b) feature extraction; (c) classification prediction.

gorithm.

Results. In this study, we use accuracy and AUC, etc. as standard evaluation metrics. The results of the 5-fold cross-validation obtained by ARM-BCS in the clinical dataset are listed in Table C1 and Figure C1, which achieved an accuracy of 90.98% and an AUC of 0.8801. We implemented hyper-parameter adjustment to achieve the goal of optimizing the model, and the experimental results are shown in Figures C2 and C3. To improve the performance of the model, we conducted an ablation study of the graph result algorithm (Figure C4). With different weight ratios, ARM-BCS is configured to achieve the best results in fusing features (Figure C5). Comparison with the inattentive features model demonstrates the enhancement of ARM-BCS performance by the attention mechanism (Table C2, Figure C6). To estimate the applicability of this classifier to the proposed model, we compare it with different classifier models (Table C3). The competitiveness of the model was demonstrated in the comparison with previous methods (Table C4).

Conclusion. This study introduces ARM-BCS, a novel attention multi-hop graph neural network model for predicting BCS. ARM-BCS utilizes real patient data obtained from the clinic to predict BCS, and it effectively captures the high-risk factors for BCS using the attention mechanism, which is essential for the accurate prediction of BCS. Moreover, ARM-BCS exhibits an extraordinary capability in handling potential correlations of multiple hops in the graph. By providing valuable insights into BCS prediction, ARM-BCS enhances our profound understanding of the complex mechanisms underlying disease occurrence.

Although ARM-BCS demonstrates potential in predicting BCS, there are also some challenges and limitations. First, the model training sample relies on real, long-tracked clinical data, which are derived from clinician records and followed up, and this reliance may increase subjectivity. Second, the time and number of patients for which the clinical data were collected are in recent years, with the result that the sample size was not sufficiently adequate. Besides, the multi-hop attentional mechanism employed by the model needs to optimize the parameters to capture the most influential critical factors, all of which are mentioned above pointing the direction for future work.

Ethics approval and consent to participate. The study protocol received approval from the ethics committee of The Affiliated Hospital of Xuzhou Medical University (Jiangsu, China; XYFY2023-KL188-01), with a waiver for informed consent.

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Supporting information Appendixes A–C. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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