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Belief rule-based inference for predicting trauma outcome

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ABSTRACT

A belief rule-based inference methodology using the evidential reasoning approach (RIMER) is employed in this study to construct a decision support tool that helps physicians predict in-hospital death and intensive care unit admission among trauma patients in emergency departments (EDs). This study contributes to the research community by developing and validating a RIMER-based decision tool for predicting trauma outcome. To compare the prediction performance of the RIMER model with those of models derived using commonly adopted methods, such as logistic regression analysis, support vector machine (SVM), and artificial neural network (ANN), several logistic regression models, SVM models, and ANN models are constructed using the same dataset. Five-fold cross-validation is employed to train and validate the prediction models constructed using four different methods. Results indicate that the RIMER model has the best prediction performance among the four models, and its performance can be improved after knowledge base training with historical data. The RIMER tool exhibits strong potential to help ED physicians to better triage trauma, optimally utilize hospital resources, and achieve better patient outcomes.

1. Introduction

Trauma has become one of the leading causes of mortality and disability worldwide. Trauma accounts for 16% of the global burden of disease, and 16,000 people die from injury daily. Death and disability from trauma frequently occur in low- and middle-income countries where approximately 90% of the total burden of trauma is reported [1,2]. In developed countries, pre-hospital triage can help stratify trauma patients into different severity levels, and different levels of trauma centers have been established to treat trauma patients with varying degrees of severity [3–5]. Unfortunately, no nationwide initial trauma assessment guidelines or tools exist to aid physicians in pre-hospital environments or emergency departments (EDs) in many less developed countries [6]. In China, a pre-hospital “120” (the ambulance call number used in China) emergency system adopts the principle of proximity to transport a trauma patient to the nearest hospital. Consequently, some severe trauma patients have been sent to low-level hospitals, which cannot treat severe trauma patients, so these patients have to be retransferred to higher-level hospitals. Trauma patient outcomes in China are relatively poor compared with those in developed countries. More than 400,000 people die from injury in China each year, and trauma is the fifth leading cause of death after malignant tumors and cardiac, cerebral, and respiratory diseases. Trauma is considered the most common cause of death of young people aged 18–40 years in China [7]. Research shows that a large proportion of in-hospital mortality can be predicted and prevented if clinical deterioration is recognized early [8,9]. Therefore, for improved patient outcomes and optimal utilization of hospital resources, physicians in EDs need to provide a rapid initial assessment of illness severity for trauma patients immediately after their arrival at the hospital, so as to make appropriate decisions regarding the treatment of patients with a high probability of in-hospital death or intensive care unit (ICU) admission [10].

Vital signs including pulse rate, systolic blood pressure, respiratory rate, body temperature, and level of consciousness are used to assign an early warning score [11–14] to assess illness severity. In trauma care, other physiological scoring tools such as the Pre-Hospital Index [15], the Trauma Index [16,17], the Glasgow Coma Score [18,19], and the Revised Trauma Score [20] have been developed to assess trauma severity before detailed diagnoses can be made for trauma patients. The nature of existing physiological trauma severity assessment tools is to assign a severity score to a patient based on physician observations and the instrumentally measured vital signs

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of the patient. However, the existing trauma scoring tools to aid physicians in EDs are most often used to stratify patients into different severity levels and rarely to predict the probability of in-hospital death and ICU admission. To explore the relationship between clinical variables available for data collection in EDs and trauma outcome, such as in-hospital death and ICU admission, logistic regression (LR) [21,22], support vector machines (SVMs) [23,24], and artificial neural networks (ANNs) [25–28] are usually employed to construct prediction models. None of the LR, SVM, or ANN models require concrete knowledge about the relationship between antecedent factors and dependent outcomes, and these methods are completely data-driven, which means sufficiently large sample data are needed to learn prediction models. The performance and efficacy of data-driven prediction models are determined not only by the learning dataset, but also by the unknown dataset to which the prediction model is applied.

In the present study, vital signs are used as antecedent factors to predict in-hospital death and ICU admission. We propose the use of a generic belief rule-based inference methodology using the evidential reasoning approach (RIMER) [29] to develop a clinical decision model. This model is aimed at helping ED physicians predict the probability of in-hospital death and ICU admission for trauma patients [30]. In RIMER, an initial belief rule base (BRB) consisting of belief rules for predicting in-hospital death and ICU admission must first be constructed based on domain expert knowledge and clinical experiences. Inference with the BRB is implemented using the evidential reasoning (ER) approach [31,32], which was originally proposed for combining multiple independent assessments of one alternative on individual criteria or attributes. The ER approach can handle both quantitative and qualitative attributes or criteria under uncertainties [33,34]. In an RIMER-based prediction model, the inputs include the clinical values of vital signs, which are used to infer with or match the belief rules in the BRB. In ER-based inference, the packet antecedent of each belief rule triggered by the inputs is considered a basic attribute with an attribute weight, which is assessed using all possible consequents with belief degrees as presented in the BRB. Thus, assessments on the packet antecedents of multiple triggered belief rules can be combined by the ER approach to achieve aggregated belief degrees in all possible consequents of the BRB. The output of the model is a combined belief degree or probability linked to the trauma outcome, including in-hospital death and ICU admission for each patient. The BRB in the model can be fine-tuned by accumulated historical data. The model is transparent in that all belief rules can be checked by experienced physicians for validity and the inference process is also transparent and can be traced for better informed decision making.

In addition, LR-based, SVM-based, and ANN-based prediction models are constructed for comparison using the same dataset, whereas the antecedent variables and dependent outcome of each of these completely data-driven prediction models are the same as those of the RIMER model. To validate the prediction performance of all RIMER-based, LR-based, SVM-based, and ANN-based models, a five-fold cross-validation method is applied.

The remainder of this paper is structured as follows. The Materials and methodology section provides a brief introduction to the following: the data source, RIMER methodology, LR analysis, SVM, ANN, five-fold cross-validation method, and area under the receiver operating characteristic (ROC) curve (AUC), which we used to measure prediction performance. The Results section compares the prediction performance of the RIMER-based model before and after BRB training, the LR-based model, an optimal SVM-based model, and an optimal ANN-based model in each training round. Discussion section elaborates on the four different types of prediction models, especially the advantages and limitations of the RIMER model. Conclusions section summarizes this study and presents conclusions drawn from the study.

2. Materials and methodology

2.1. Dataset

A sample of trauma patients sent to Kailuan Hospital, North China, between 2008 and 2009 was employed for prediction model development and validation. Patients were included for analysis if they met the following criteria: (a) directly sent to the ED from an accident site; (b) with the five vital signs recorded upon their arrival at the ED; and (c) possible to retrieve corresponding in-hospital data. No further restrictions were made on the severity or characteristics of the cases. A total of 1299 trauma patients were directly sent to the ED at Kailuan Hospital within the sampling period, among which 1190 (91.61%) had both ED vital signs data and in-hospital data. The remaining 109 patients had either missing data on vital signs or missing in-hospital data, so they were excluded from data analysis.

The primary outcome of this study is a composite one, including in-hospital death and ICU admission.

2.2. RIMER methodology

In the RIMER methodology, traditional IF-THEN rules are extended to belief rules by embedding belief degrees in all possible consequents of a rule. Meanwhile, other knowledge representation parameters, including rule weights, antecedent attribute weights, and consequent belief degrees, are embedded in the belief rules. Inference with a BRB in a RIMER system is implemented using ER. The RIMER system presents the advantages of using belief rules to represent clinical domain knowledge under uncertainty and inference with uncertain clinical data using the ER approach. The knowledge representation parameters, including rule weights, antecedent attribute weights, and consequent belief degrees in the BRB, can be fine-tuned or trained using accumulated historical data [35]. The RIMER methodology has been employed to stratify patients with cardiac chest pain [36,37], diagnose lymph node metastasis in gastric cancer [38,39], and many other areas [40–42]. A brief introduction to BRB, inference with BRB, and the training of BRB follows.

2.2.1. BRB

A belief rule can be described as R_k:

$$\text{If}\, A_1^k \wedge A_2^k \wedge \cdots \wedge A_{T_k}^k,$$
$$\text{then}\ \{(D_1, \beta_{1k}), (D_2, \beta_{2k}), \ldots, (D_N, \beta_{Nk})\} \left(\beta_{jk} \geq 0, \sum_{j=1}^{N} \beta_{jk} \leq 1 \right),$$
$$\text{with a rule weight}\ \theta_k\ \text{and attribute weights}\ \delta_1, \delta_2, \ldots, \delta_{T_k}, \quad k \in \{1, \ldots, L\}, \tag{1}$$

where $A_i^k (i = 1, \ldots, T_k)$ is the referential category or grade of the ith antecedent attribute used in the kth rule; $\beta_{jk} (j = 1, \ldots, N; k = 1, \ldots, L)$ is the belief degree assigned to consequent D_j, and it can initially be given by experts; $\delta_i (i = 1, \ldots, T_k)$ is the antecedent attribute weight representing the relative importance of the ith attribute; and θ_k is the rule weight representing the relative importance of the kth rule. L represents the number of all belief rules in the rule base. T_k is the number of all antecedent attributes used in the kth belief rule. N is the number of all possible consequents in the BRB. Traditional IF-THEN rule can be represented as a special case of belief rule with only one consequent, and the consequent belief degree is always 100%.

Initial belief rules in this study were provided by domain experts, and the five vital signs, namely, body temperature, respiratory rate, systolic blood pressure, pulse rate, and level of consciousness, are used as antecedent factors in the rule base. The possible consequents of the rule base include “occurrence of in-hospital death or ICU