Original Article

# Do clinical and paraclinical findings have the power to predict critical conditions of injured patients after traumatic injury resuscitation? Using data mining artificial intelligence

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## ARTICLE INFO

## ABSTRACT

*Purpose:* The triage and initial care of injured patients and a subsequent right level of care is paramount for an overall outcome after traumatic injury. Early recognition of patients is an important case of such decision-making with risk of worse prognosis. This article is to answer if clinical and paraclinical signs can predict the critical conditions of injured patients after traumatic injury resuscitation.
*Methods:* The study included 1107 trauma patients, 16 years and older. The patients were trauma victims of Levels I and II triage and admitted to the Rajaee (Emtiaz) Trauma Hospital, Shiraz, in 2014–2015. The cross-industry process for data mining methodology and modeling was used for assessing the best early clinical and paraclinical variables to predict the patients' prognosis. Five modeling methods including the support vector machine, K-nearest neighbor algorithms, Bagging and Adaboost, and the neural network were compared by some evaluation criteria.
*Results:* Learning algorithms can predict the deterioration of injured patients by monitoring the Bagging and SVM models with 99% accuracy. The most-fitted variables were Glasgow Coma Scale score, base deficit, and diastolic blood pressure especially after initial resuscitation in the algorithms for overall outcome predictions.
*Conclusion:* Data mining could help in triage, initial treatment, and further decision-making for outcome measures in trauma patients. Clinical and paraclinical variables after resuscitation could predict short-term outcomes much better than variables on arrival. With artificial intelligence modeling system, diastolic blood pressure after resuscitation has a greater association with predicting early mortality rather than systolic blood pressure after resuscitation. Artificial intelligence monitoring may have a role in trauma care and should be further investigated.
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## Introduction

Trauma is one of the most important causes for the loss of life in the world[1,2] and proper treatment and appropriate facilities in the early hours after trauma can considerably reduce morbidity and mortality. Finding injured and ill patients is a critical job and transferring them fast to centers or to ICUs is directly related to a therapist's skill or experience.

Many studies[3–7] have been conducted to find the reliable indicators to predict the illness of trauma patients and it was found that these indicators could have a high positive predictive value or a negative predictive value. Predictive scoring systems also have been developed but a 100% index and scoring system has not been found to be accepted for predicting the severity of acute traumatic injury. Perhaps it is because of the complexity of the human biological system that the different forms of trauma create a variety of clinical protests by their impact on various body systems.

The perfect time to understand the complexity of the reaction is when the human body is activated by different types of damage with different compensatory mechanisms affecting the clinical and paraclinical findings. Therefore, what we see and measure is the

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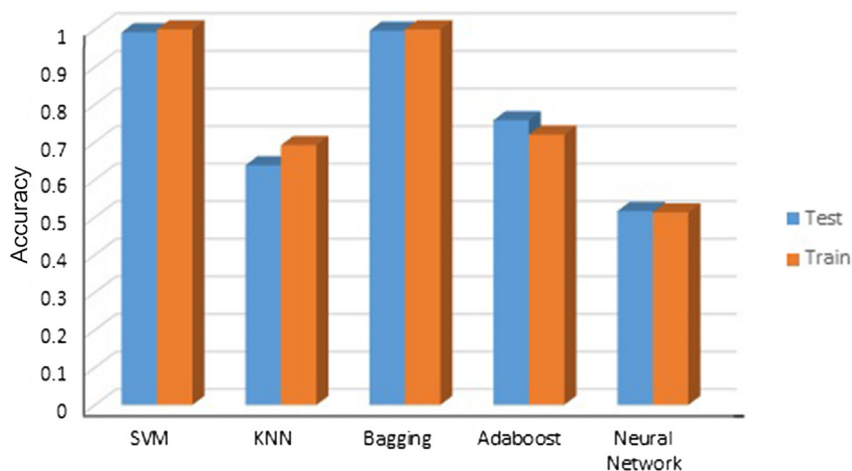Peer review under responsibility of Chinese Medical Association.

**Fig. 1.** Comparison of the accuracy of classification methods. SVM: support vector machine; KNN: k-nearest neighbors algorithm.

outcome of various body processes and different responses to injury in different phases. Therefore, the lack of conclusions from data monitoring by using linear statistics could be due to the complexity of the trauma, body systems involved, and the body's compensatory response in trauma victims in different phases. In this case, the use of modeling may help by intelligent systems with a better understanding of the clinical and laboratory status of each component, making it possible to more accurately predict outcomes.[8]

In many medical fields, the use of intelligence systems is not new to predict the course of a disease. Artificial intelligence forecasting systems have been abundantly used in various forms of cancer diseases[8–10] including breast cancer, epidemic diseases, as well as chronic diseases with emergency conditions.

In this study, we try to find the important predictive factors by examining the clinical and paraclinical data of multiple blunt trauma injuries on admission after initial resuscitation by using intelligence system model. Then, we will try to predict the likely severity of injuries by supervised learning algorithms and compare them with the common indicators.

## Methods

### Study design

All the trauma patients of over 16 years were included in the study, who had been admitted to the Rajaee Trauma Hospital, Shiraz, with Levels I and II triage in 2014 and 2015. Patients with incomplete data and victims who were dead on arrival were excluded of the study.

All the patients admitted to Rajaee Trauma Hospital were treated for trauma based on ATLS 9[th]edition. Every information pertaining to the patient's clinical data was extracted on arrival and after the initial resuscitation from patient records and the Hospital Information System (HIS). The information concerned the vital signs, injured organs, Injury Severity Score (ISS) data. A total of 67 features (Fig. 1) were studied. Patients were divided into two groups: critically ill victims and non-critically ill victims. Critically ill patients were victims who had died on the first day in the hospital or were transferred to the ICU or for emergency surgery. Other injured, who were non-critically ill patients, were not shifted to the ICU and no emergency surgery was done on them.

### Data collection

Data and the characteristics of the research were determined under the supervision of a trauma specialist. Then the form containing features were provided. Data were collected and forms were filled. Some of the data in the form were provided by a knowledgeable medical scientist and the other parts were extracted from the HIS hospital software according to patient's record. The collected data were compiled in the form provided by Excel.

### Procedure

After the completion of collecting data, the selection and application of data mining techniques were carried out. At this stage, clean data were searched for the desired patterns. Therefore, the extracted information was analyzed according to the primary objectives and the best results were analyzed to achieve the best model.

A total of 1,600 patients in levels I and II triage who admitted to the trauma center of Rajaee Hospital in Shiraz were selected. After data preparation, they were sent to the Artificial Intelligence System for processing. As we said before, ill and non-critically ill patients were classified into two groups. Then, 70% of the data were considered as training data and 30% as an assessment.

### Statistical analysis

To implement the various techniques in this study, we used the MATLAB and WEKA version 3-7-12 software.[11] Fig. 2 is the age data of the injured, with missing values being filled to the median value. The heart rate data is shown in Fig. 3, with the missing values filled with mean. Fig. 4 is data on the airway specificity of the injuries whose missing values are filled with mode. For classifying the patients and predicting their prognosis, five modeling methods were compared: the support vector machine, K-nearest neighbor algorithms, Bagging and Adaboost, and the neural network. For all algorithms, different parameters were considered to select the best parameter and ultimately, the error of experimental data and the error of training data were compared. Some parameters such as the error rate between testing and training datasets, Recall and F-Measures values were applied for evaluating the models. Then, among the different search methods, the best features were selected by the best greedy stepwise and linear forward selection,
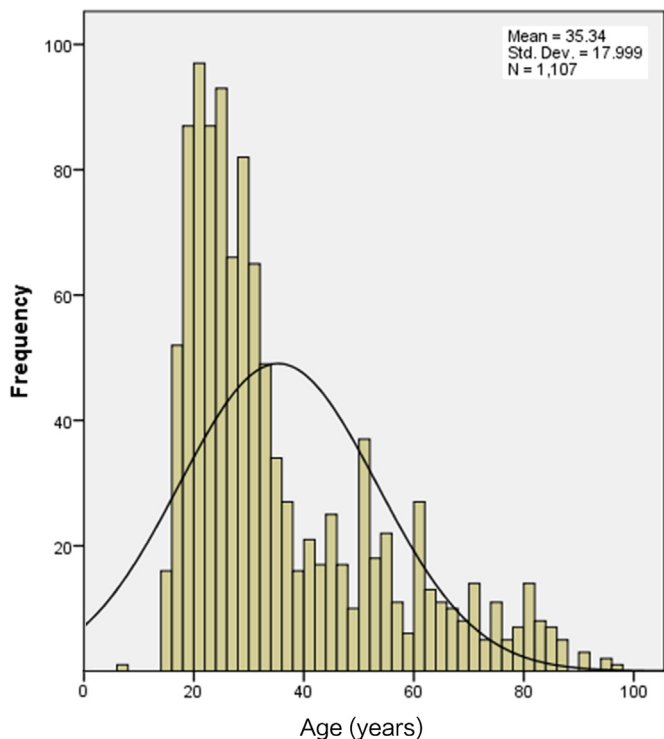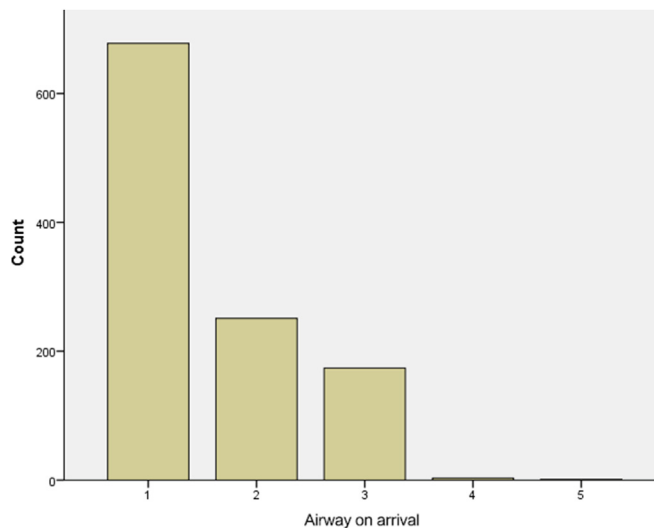
**Fig. 2.** Age data feature.

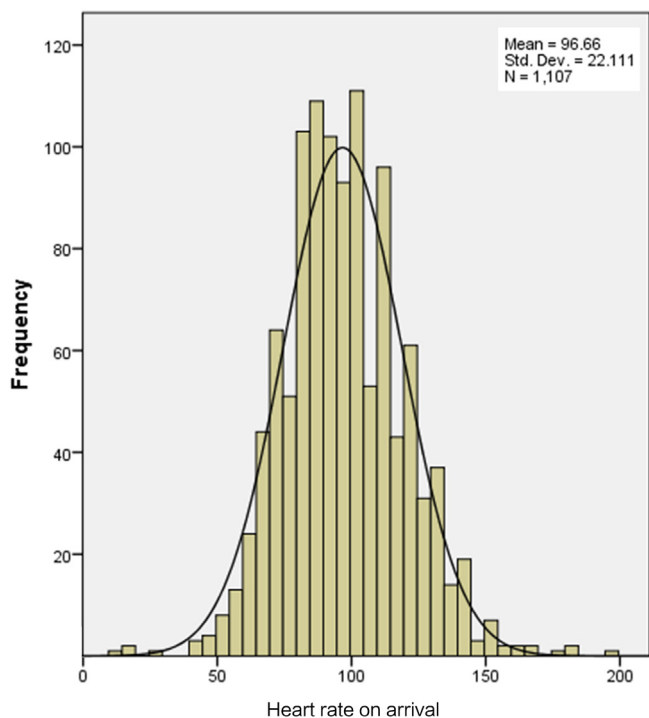and the chi-square method was used for ranking. In addition, an



**Fig. 3.** Heart rate on arrival data feature.

independent two-sample $t$-test was applied to compare the average values of the two patient groups. The significant level was 0.05.



**Fig. 4.** Airway on arrival feature data.

## Results

Altogether 1107 patients met the inclusion criteria and their data were reviewed and analyzed. There were 638 patients in the critically ill group and 469 patients in the non-critical ill group. The average ages of the first group (critically ill patients) and second group (non-critically ill patients) were 35.57 and 35.01 years respectively ($p = 0.608$) and the male-to-female ratio was 6.41. The mean values of the base excess (BE) in each group were −4.2 for critically ill patients and −2.35 for ill patients, which revealed a significant difference ($p < 0.0001$). Base excesses after resuscitation were −6.28 in the first group and −3.44 in the second, and the difference was significant ($p < 0.0001$). The averages of Glasgow Coma Scale (GCS) score were 10.35 and 13.84 respectively, and that was a significant difference between the two groups ($p < 0.0001$) (Table 1). Moreover, the GCS after resuscitation in both groups were 9.86 and 13.91, and the difference was significant ($p < 0.0001$).

After the model classification, methods were used by artificial intelligence to analyze the data. The results of the classification methods on our datasets are shown in Table 2.

Then, the data were ready for use by the cross-industry process for data mining (CRISP-DM) model for data mining techniques. CRISP is one of the most practical ways to carry out data mining

**Table 1**
Characteristics of the study population of 1107 trauma patients on arrival (mean ± SD).

| Variables | Non-critical ($n = 469$) | Critical ($n = 638$) | $p$ value |
|---|---|---|---|
| Age (year) | 35.01 ± 17.24 | 35.57 ± 18.55 | 0.608 |
| Heart rate (beats/min) | 92.62 ± 18.71 | 99.63 ± 23.89 | <0.0001 |
| Systolic blood pressure (mmHg) | 125.93 ± 19.87 | 123.09 ± 27.67 | 0.059 |
| Diastolic blood pressure (mmHg) | 78.39 ± 13.96 | 78.23 ± 17.96 | 0.874 |
| Respiratory rate (breaths/min) | 19.62 ± 8.48 | 20.24 ± 10.14 | 0.283 |
| SatO$_2$ (%) | 93.81 ± 5.93 | 91.38 ± 8.60 | <0.0001 |
| Glasgow coma scale | 13.84 ± 2.17 | 10.35 ± 4.22 | <0.0001 |
| pH | 7.36 ± 0.08 | 7.33 ± 0.11 | <0.0001 |
| HCO$_3$ (mmol/L) | 22.51 ± 3.92 | 21.07 ± 4.42 | <0.0001 |
| PCO$_2$ (mmHg) | 39.78 ± 9.16 | 39.79 ± 10.23 | 0.990 |
| Base excess (mmol/L) | −2.35 ± 3.48 | −4.20 ± 4.79 | <0.0001 |
| HCT (%) | 42.29 ± 7.84 | 39.37 ± 8.06 | <0.0001 |
| SO$_2$C (%) | 65.27 ± 25.40 | 64.90 ± 28.79 | 0.821 |

**Table 2**
The results of classification methods. (mean ± SD)

|                | Test            | Train           | Recall | F-measure |
|----------------|-----------------|-----------------|--------|-----------|
| SVM            | 0.9924 ± 0.02   | 1.0000 ± 0.00   | 0.6940 | 0.7640    |
| KNN            | 0.6384 ± 0.02   | 0.6918 ± 0.01   | 0.7427 | 0.7056    |
| Bagging        | 0.9967 ± 0.00   | 1.0000 ± 0.00   | 0.9804 | 0.9896    |
| Adaboost       | 0.7581 ± 0.01   | 0.7197 ± 0.01   | 0.7210 | 0.7220    |
| Neural network | 0.5160 ± 0.07   | 0.5128 ± 0.07   | 0.5769 | 0.6045    |

SVM: support vector machine; KNN: k-nearest neighbors algorithm.

projects that are most used among other methods. This methodology is a powerful and flexible way to improve the desirability of data mining in solving organizational problems.

According to Table 2, bagging algorithm has the best result (98%) among the algorithms used, followed by the SVM method with 76% accuracy to predict illness of patients (Fig. 1). Then, the best features selected including best greedy stepwise and linear forward selecting methods. And the chi-square ranking method was used to determine the order of importance of each feature. In all the ranked sets, the index after resuscitation included GCS, HCT, diastolic BP, BE, pH, $PO_2$ and $HCO_3$ with high ratings.

## Discussion

The present study found patterns to predict early 24 h' conditions through better accuracy of the anatomical and physiological findings. We also found that using the SVM and bagging algorithm predict the traumatic situation of patients with a precision of 99%.

The other pattern obtained from the study showed that the patients' diastolic pressure is more important than systolic pressure because of GCS (the level of consciousness) and blood gas after initial resuscitation of the patients. These two items indicate deterioration due to unreasonable initial damage or non-severe damage. Diastolic pressure was significant in artificial intelligence modeling and algorithms. In Table 1, the data were analyzed by using ordinary statistical formula. Therefore, the injured persons were entered an irreversible phase. This is the point that has been never mentioned in any of the previous studies or scoring systems to determine the hospital prognosis.

Experimental results reveal the reflex of different organs into internal and external inputs within the body. Therefore, as soon as a change becomes wider or stronger, the number of subsystems involved in creating responses increases.[12]

In several studies,[8,12–21] the use of artificial intelligence systems has proved to be effective in predicting a trauma patient's condition including the prediction of death, need for blood transfusion, etc. The use of artificial intelligence systems makes the work of health care system easier in matters of taking decisions.

In present study, the high power of Bagging algorithm to predict the condition of patients in the first 24 h after admission can help the medical team in adopting the treatment pathway. Since it is proven that one of the most important indicators of the best treatment for traumatic injury is the immediate transfer of the injured to a trauma treatment center, the referring of an injured patient to a non-trauma center is immediately screened with the help of the available clinical and paraclinical parameters. The feeding of that data into the application enables the intelligent system to make an accurate prognosis about the injured patient's condition. This helps in promptly sending the patient to the proper hospital before conditions deteriorate.

As mentioned before, conventional factors' predictive power such as GCS upon arrival and BE is much lower than the power of artificial intelligence of Bagging algorithm.

The comparison of clinical and paraclinical factors after resuscitation with value at arrival time has shown the higher predictive power which is marked in this model by intelligence system.

As originally stated, what we see in clinical and paraclinical indicators are the results of trauma to the body and compensatory responses of the various systems of the injured body. Therefore, the condition of these systems is crucial for receiving treatment by patients. If compensation system such as the endothelial system does not fail, conditions would improve with supportive measures, but if the compensation systems fail, resuscitation performance cannot improve the conditions. In such an event, the clinical and paraclinical condition of injured patients may be the same in both cases.

A study showed that the benefit of lower diastolic blood pressure is limited to the range of 70–85 mmHg with a significant trend of 60–65 mmHg. Any value of diastolic blood pressure less than 60 mmHg will increase the likelihood of all-cause mortality.[22] Further, it showed that low diastolic blood pressure may only be harmful in patients with diabetes or as a consequence of antihypertensive therapy.[22,23]

Diastolic blood pressure is an important predictor of mortality in younger adults and provides little independent mortality risk information in adults over 50 years old.[24]

The other finding of this mode shows the importance of diastolic blood pressure compared to the systolic blood pressure in patients and its impact on the outcome. Especially, diastolic blood pressure after resuscitation has the high power to predict the future condition of the injured in the modeling. Diastolic blood pressure, particularly diastolic pressure after resuscitation, reflects the condition of vascular endothelium, e.g. whether they are alive and reactive. So, it is not surprised that this indicator is given such a place in modeling.

In conclusion, the benefits of intelligent systems and supervised learning algorithm can predict the outcome of patients (favorable/unfavorable) by using GCS, BE and diastolic blood pressure after resuscitation. It can help to predict the probability of the injured critically ill patients and the need for the invasive diagnostic and therapeutic procedures. Artificial intelligence algorithms can be converted into a software program and the medical team can make decisions, especially at times and places where less experienced people in centers need to decide to keep the injured or refer them to more equipped facilities by identifying the patient's misconduct. Therefore, we showed the potential artificial intelligence ability to predict injury outcome and assist decision-making for the injured, especially at level 3 or 4 trauma centers.

## Funding

## Ethical statements

Informed consent has been obtained from the patients.

## Declaration of competing interest

There is no conflict of interest.

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