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ORIGINAL RESEARCH

Extracting the Factors Affecting the Survival Rate of Trauma Patients Using Data Mining Techniques on a National Trauma Registry

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Abstract: **Introduction:** Thousands of people die due to trauma all over the world every day, which leaves adverse effects on families and the society. The main objective of this study was to identify the factors affecting the mortality of trauma patients using data mining techniques. **Methods:** The present study includes six parts: data gathering, data preparation, target attributes specification, data balancing, evaluation criteria, and applied techniques. The techniques used in this research are all from the decision tree family. The output of these techniques are patterns extracted from the trauma patients dataset (National Trauma Registry of Iran). The dataset includes information on 25,986 trauma patients from all over the country. The techniques that were used include random forest, CHAID, and ID3. **Results:** Random forest performs better than the other two techniques in terms of accuracy. The ID3 technique performs better than the other two techniques in terms of the dead class. The random forest technique has performed better than other techniques in the living class. The rules with the most support, state that if the Injury Severity Score (ISS) is minor and vital signs are normal, 98% of people will survive. The second rule, in terms of support, states that if ISS is minor and vital signs are abnormal, 93% will survive. Also, by increasing the threshold of the patient's arrival time from 10 to 15 minutes, no noticeable difference was observed in the death rate of patients. **Conclusion:** Transfer time of less than ten minutes in patietns whose ISS is minor, can increase the chance of survival. Impaired vital signs can decrease the chance of survival in traffic accidents. Also, if the ISS is minor in non-penetrating trauma, regardless of vital signs and if the victim is transported in less than ten minutes, the patient will survive with 99% certainty.

Keywords: Data Mining; Survival; Mortality; Trauma Severity Indices; Injuries; Injury Severity Score

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1. Introduction

Nowadays, most people are exposed to various accidents. Thousands of people die due to these accidents all over the world every day, which leaves adverse effects on families and the society. These accidents can include Disasters (natural ,man-made), traffic accidents, and falls from a height (FFH). The outcome of such incidents on humans is called trauma, in case that is inflicted on the body from outside (1, 2). Acute trauma such as motor vehicle collision (MVC), stab wounds, falls, and similar events can be fatal (3). Early identification of trauma patients who are at risk of death is very important for clinical decision-making (4). Data mining is one of the approaches that is used in various fields of medicine, including trauma management (5, 6). Various researches have been done in this field. Yadalhi's study showed that the Injury severity score (ISS) index depicts an increase in trauma

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patients mortality rate. Yet, an increase in the Glasgow coma scale (GCS), and the Revised trauma score (RTS) and Trauma injury severity score (TRISS) indices reduces the risk of mortality. It is worth mentioning that the TRISS index is better than other indices in assessing the severity of injury caused by trauma (7).

Hassanzadeh examined 1043 trauma patients and identified the factors affecting the mortality of patients. He used data mining techniques such as decision trees, k-nearest neighbors, and neural networks (8). Liu used a review study to compare data mining techniques in predicting trauma outcomes. Outcomes included survival/mortality, length of hospital stay, and traumatic brain injuries (9). Rao investigated a model for predicting mortality from severe and moderate brain injury. He used logistic regression, support vector machine, decision tree, naive-Bayes, and neural networks. The neural network had the best performance for predicting mortality due to trauma (10). Trauma registries are one of the important sources of information that help check the quality of provided health care services. It also provides valuable perspectives to improve the quality of care (11). The main purpose of this study was to identify the factors affecting the survival of patients following trauma. This study aimed to identify the factors affecting the mortality of trauma patients using data mining techniques.

2. Methods

2.1. Study setting and design

The study includes six parts: information collection, data preparation, specifying target attributes, data balancing, evaluation criteria, and applied techniques. The output of these techniques are patterns extracted from the trauma patients dataset (National Trauma Registry of Iran). The dataset includes information on 25,986 trauma patients from all over the country. The techniques that were used include random forest, CHAID, and ID3.

This study does not contain any studies with human participants or animals performed by any of the authors. The protocol of study was approved by Ethics committee of Isfahan University of Medical Sciences (Ethical Code: IR.MUI.NUREMA.REC.1400.044).

2.2. Data gathering

Eligibility criteria and sources and methods of selection of participants were:

1. Trauma patients who were hospitalized for more than 24 hours.
2. Trauma patients who died in the emergency department and were hospitalized for less than 24 hours.
3. Trauma patients transferred from the previous hospital intensive care unit (ICU) to current hospital ICU with length of stay of less than 24 hours.

The dataset includes information on 25,986 trauma patients from all over the country. The dataset was imbalanced so that the number of people who died was approximately 2% of the dataset and 98% of the victims were alive. The dataset had 132 attributes. After consulting with an emergency medicine specialist, the number of attributes was reduced to 23 items. These attributes include the patient's age at the time of injury, ISS, vital signs, the time interval between the occurrence of the injury and arrival at the emergency department (minutes), history of hospitalization due to trauma, the initial diagnosis of injury, cause of trauma, number of hospitalizations due to trauma, approximate height of the fall in meters, the position of the injured person, and if the victim is a non-passenger, select the role of the injured person and the type of accident. When the type of accident was a collision, select the type of opposite object.

If the injured person was a passenger in a car or motorcycle/bicycle, were appropriate safety devices used at the time of the accident? Were safety belts used?

If the injured person was a child younger than 8 years old in a car or motorcycle/bicycle, child seats; were appropriate safety devices used at the time of the accident?

If the injured person was a passenger of a car, were appropriate safety devices such asairbags used when the accident occurred?

If the injured person was a passenger of a motorcycle/bicycle, were appropriate safety devices such as helmets used when the accident occurred?

In case of transfer between centers, was the patient transferred from another intensive care unit by ambulance to the current facility ICU? What was the primary Eye score (at the scene of the accident), the primary Verbal score (at the scene of the accident), the primary Motor score (at the scene of the accident), and initial total GCS (at the scene of the accident).

2.3. Data preparation

The ISS attribute has numerical values. The values between 1 and 8 were categorized as minor, values 9 to 15 as moderate, values 16 to 24 as severe, and 25 and above as very severe. The attribute of the time interval between the occurrence of injury and reaching the emergency department (minutes) was divided into two periods of less than 10 minutes and more than 10 minutes. Also, the age of the patient at the time of injury was divided into three periods: less than 8 years (children) and 8 to 18 years (adolescents), and more than 18 years (adults). Records with missing values in more than 25 percent of attributes were removed.

2.4. Identification of target attributes

The survival attribute, which was a binary attribute, was used as the target attribute. The survival attribute had two values:

survival and death.

2.5. Balancing data

The dataset was imbalanced. In order to avoid this variance to a feasible extent, it was necessary to use the Bootstrap sampling technique (AdaBoost).

2.6. Evaluation criteria

The target group contains a binary class with two values, alive and dead. Various criteria were used for evaluation. One of these criteria was accuracy. The closer the accuracy of this criterion, the better the result would be. This criterion was calculated based on the following formula:
Accuracy = (TP+TN)/(TP+TN+FP+FN)
The TP (true positive) identifies the number of records that the group has correctly placed as dead. TN (true negative) identifies records that have been correctly identified as survived individuals. FN (false negative) identifies records that have been incorrectly identified as survived, and FP (false positive) identifies the number of records that have been incorrectly identified as dead.
Sensitivity (True Positive Rate) is the ratio of true predicted positive instances to the total of actual positive instances.
These parameters can be calculated using Equations: Sensitivity=TP/(TP+FN)
Precison (positive predictive value) is the ratio of true predicted positive to the total of predicted positive instances. Precsion = TP/(TP+FP)
The support criterion specifies the number of repetitions of the combination of assumptions of a rule.
The confidence criterion indicates for how many percent of people with the mentioned assumptions, the result is valid.
In the evaluation stage, 25986 samples and 23 attributes are considered. The 10-fold cross-validation method was used to divide the dataset into training and test sets. Based on this, the 25986 existing samples are divided into 10 groups. During 10 repetitions of the experiment, each time 9 groups make up 90% of the original dataset as the training dataset, and one remaining group makes up 10% of the original dataset, which is considered a test dataset. The training dataset is used to generate input patterns to build the classification model and the test dataset was used to evaluate its accuracy.

2.7. Data mining techniques

The techniques used in this research are all from the decision tree family. The output of these techniques is a set of rules extracted from the dataset of trauma patients. In the structure of the decision tree, by moving deeply from the root node to the leaf node, the assumptions of the rules were extracted. The techniques that were used include random forest, CHAID, and ID3. The random forest technique is also one of the techniques applied in the field of data mining. The random forest technique is often more accurate than a single classifier. This technique can manage data without preprocessing, and the need for data reduction and transformation. It operates by constructing a multitude of decision trees at training time . For classification tasks, the output of the random forest is the class selected by most trees.
CHAID is a decision tree-based method, in which the data space is divided into similar subsets in different iterations. This algorithm uses the Chi-2 test to decide on each partition for partitioning. CHAID analysis builds a predictive model, or tree, to help determine how variables best merge to explain the outcome in the given dependent variable.

3. Results

3.1. Baseline characteristics of patients

Twenty-three attributes were considered predictors. Table 1 shows attributes, values, and numbers. The number of adults was 4 times the number of children, and ISS for the majority of people who were brought to the emergency department (ED) or ICU was considered as minor. Also, the number of people with normal and abnormal vital signs was almost equal. The attribute of the time interval between the occurrence of injury and reaching the emergency department (minutes) had a large number of missing values. Among the people whose information was registered, 2732 people had reached the emergency department in less than 10 minutes. With regard to the cause of trauma, road traffic accidents were the most common reason.

3.2. Fidings of data mining techniques

As shown in Table 2, in terms of accuracy, random forest performs better than the other two techniques. The ID3 technique performs better than the other two techniques in terms of the dead class. The random forest technique has performed better than other techniques in the living class.
Table 3 shows rules derived from applying different data mining techniques to the data set. The confidence (10) column means that the confidence is computed based on a 10-minute threshold for patient arrival. Moreover, the confidence (15) column means that the confidence is computed based on a 15-minute threshold for patient arrival. The rules are arranged in descending order, based on the amount of support. As shown in Table 3, the rule with the most support, states that if ISS is minor and vital signs are normal, the patient will survive with 98% confidence. The second rule, in terms of support, states that if ISS is minor and vital signs are abnormal, the patient will survive with 93% confidence. Also, by increasing the threshold of the patient's arrival time from 10 to 15 minutes, no noticeable difference was observed in the death rate of patients. We had just three changes in the confidence level, and in some cases, the confidence level re-

Table 1: Attributes, values, and numbers extracted from trauma registry

Attributes	**Value (number)**
Age	Children (2558) Adolescents (2326) Adults (21054)
Injury severity score (ISS)	Minor (21300) Moderate (4342) Severe (209) Very severe (134)
Vital Signs	Normal (13093) Abnormal (12891)
Time interval between the occurrence of the injury and arrival at the emergency department (minutes)	<10 minutes (2372) 10-20 minutes (99) 20-30 minutes (34) 30-60 minutes (28) >60 minutes (41)
History of hospitalization due to trauma	Yes (4434) No (21434)
Initial diagnosis of damage	Amputation (59) Fracture (8734) Tearing (662) Trauma (94) Foreign body (101) Dislocation (206) Laceration (924)
Cause of trauma	Non-penetrating traumas (Building collapse, crush injuries,...) (2176), electrical injuries (26), animal attack (bites, paws, horns, etc.) (93), road traffic accidents (10251), suffocation (any type of respiratory arrest) (7), direct burn (cigarette, fire, flame) (75), fall (8789), sharp force trauma (cut, ...) (3682), blast injuries (16), animal bites (4), indirect burns (contact with heat, boiling water) (117), poisoning (inhalation, drugs, etc.) (44), drowning and submersion (5), unknown factors (14)), other transport accidents (non-road accidents: train, plane, ship) (201), and other (310)
Number of admissions due to trauma	Once (3532) Twice (632) Three times (164) Four times (57) Five times (24) Six times (7)
Approximate height of fall in meters	Less than or equal to one meter (6274) Between one and two meters (1063) Between two and three meters (614) Between three and four meters (264) More than four meters (408)
The position of the injured person	Cyclists (160), bus passengers (31), car passengers (1614), van passengers (57), heavy vehicle passengers (63), pedestrians (2220), and motorcyclists (2375)
If the position of the person is non-pedestrian, choose the role of the injured person	Passenger (1414) Driver (2682)
Type of incident	Collision (crash) (4256) Rollover (1205)
If the incident type is a collision, select the object type	Bicycle (16), van (3073), fixed object (283), pedestrian / animal (43), train (1), motorcycle (501), and heavy transport vehicle (188)
If the injured person is a passenger of a car or motorcycle/bicycle, were appropriate safety devices used during the accident?	Yes (660) No (25324)
If the injured person is a passenger (less than 8 years) in a car, were appropriate safety devices used during the accident? Child seat?	Yes (2) No (25982)
If the injured person is a passenger in a car, were appropriate safety devices used during the accident? Airbag?	Yes (54) No (25930)
If the injured person is a passenger on a motorcycle/bicycle, were appropriate safety devices used during the accident? Helmet?	Yes (472) No (25512)
Transfer between centers (was the patient transferred to your facility by ambulance from another intensive care unit?)	Yes (4086) No (13189)
Glasgow Coma Scale (GCS) or Early Eye GCS (at the scene of the accident)	Does not open the eyes (52) Opens the eyes in response to pain (67) Opens the eyes in response to sound (177) The eyes are open spontaneously and without external stimulation (6935)
Glasgow Coma Scale (GCS) or Early Verbal GCS (at the scene of the accident)	No sound is produced (43) Incomprehensible sound (45) Using inappropriate words (86) Confused conversation (237) The victim is fully aware of time and place (6811)
Glasgow Coma Scale (GCS) or Early Motor GCS (at the scene of the accident)	Complete relaxation and immobility of the limbs (25) Extends the limbs in response to pain (22) Flexes the limbs in response to pain (55) Withdraws from the painful stimulus (72) Localization of the painful stimulus (183) Obeys the examiner's commands (6870)
Glasgow Coma Scale or initial total GCS (at the scene of the accident)	Mild brain injury (14H15) (6949) Moderate brain Injury (9H13) (158) Severe brain injury (less than 9) (8)
Survival state	Survived (228) Died (25757)

Table 2: Sensitivity, precision and accuracy of data mining techniques

Methods	Sensitivity (95% CI)		Accuracy (95% CI)
	Dead	Alive	
96.53 (96.02 -97.04)	98.75 (98.3-99.2)	20.35 (18.25- 22.45)	Random Forest
95.96 (95.56-96.36)	98.22 (97.67-98.77)	38.10 (36.30-39.90)	ID3
96.12 (95.74-96.5)	98.53 (98.02-99.04)	25.52 (23.52-27.52)	CHAID
99.53 (99.32-99.74)	99.75 (99.68-99.82)	15 (13.5-16.5)	Random Forest + AdaBoost
99.16 (98.82-99.5)	99.51 (99.34-99.68)	28.57 (25.48-31.66)	ID3 + Adaboost
99.26 (98.95-99.57)	99.97 (99.95-99.99)	7.14 (6.78-7.5)	ChaiD + boosting

Data are presented with 95% confidence interval (CI).

Table 3: Rules derived from applying different data mining techniques to the data set

Conditions	Co10	Su10	Co15	Su15
If ISS is minor and vital signs are normal	0.98	11352	0.98	11352
If ISS is minor and vital signs are abnormal	0.93	9948	0.93	9948
If ISS is minor, the person is an adult, and vital signs are normal	0.98	9078	0.98	9078
If ISS is moderate and vital signs are normal	0.97	2686	0.97	2686
If ISS is moderate and vital signs are abnormal	0.92	1656	0.92	1656
If ISS is minor, the person is an adult, and vital signs are abnormal	0.93	8271	0.92	8271
If the person is an adult, the vital signs are normal, and the patient's arrival time is ≤10 minutes	0.96	8246	0.94	8257
If ISS is minor, the person is an adult, vital signs are abnormal, and the patient's arrival time is ≤10 minutes	0.94	7407	0.91	7416
If ISS is minor, the person is an adult, vital signs are normal, and the patient's arrival time is ≤10	0.98	7164	0.97	7167
If ISS is minor and the person is a child	0.99	3951	0.99	3951
If ISS is minor, the person is an adult, the cause of the trauma is a road traffic accident, vital signs are abnormal, and the patient's arrival time is ≤10 minutes.	0.97	3754	0.95	3785
If ISS is moderate and the patient's arrival time is less than or equal to 10 minutes	0.92	3462	0.92	3481
If the person is an adult, the cause of the trauma is a road traffic accident, the vital signs are normal, and the patient arrives in ≤10 minutes.	0.99	3146	0.98	3234
If ISS is moderate, the person is an adult and vital signs are abnormal	0.92	2435	0.92	2435
If ISS is minor, the person is an adult, vital signs are normal and arrival time is more than 10 minutes	0.99	1914	0.99	1987
If ISS is minor, the person is an adult, the cause of the trauma is blunt force trauma (cut), vital signs are normal, and the patient's arrival time is ≤10 minutes	0.99	1585	0.99	1615
If ISS is moderate, the person is an adult, and vital signs are normal	0.94	1358	0.94	1358
If the person is a teenager, the cause of the trauma is a blow (cut), vital signs are abnormal, and the patient reaches ≤10 minutes	0.99	1094	0.98	1213
If the person is an adult, the cause of the trauma is non-penetrating injuries, the vital signs are normal, and the patient reaches the destination in ≤10 minutes	0.99	788	0.99	829

Data are presented as survival rate and number of cases. Rules with more than 90% confidence were introduced. Co: confidence; Su: support; Co10 and Co15: means that the confidence is computed based on a 10- and 15-minute threshold for patient arrival; Su10 and Su15: means that the support is computed based on a 10- and 15-minute threshold for patient arrival. ISS: injury severity score.

mained constant. The biggest change was related to the rule (if ISS is minor, the person is an adult, vital signs are abnormal and the patient's arrival time is less than or equal to 10 minutes, then the person will survive). In this rule, the confidence changed from 94 to 91 percent.

4. Discussion

In this study the data of 25,986 trauma patients were analyzed in an imbalanced dataset. The applied techniques were random forest, CHAID, and ID3. Among the 132 attributes of the examined patients, 23 were selected as the most relevant. According to the results, random forest performed better than the other two techniques, in terms of accuracy. In this study, the accuracy and sensitivity of random forest were 96.53% and 98.75%, respectively. We investigated the condition of trauma patients throughout the country (Iran). So far, no such study has been conducted in Iran on this dataset using this number of records. Also, in this study, rules were extracted that can help doctors in diagnosing the survival of trauma patients based on confidence and support criteria.

By applying data mining techniques to the dataset, 21 rules were extracted. To check the obtained rules and select the most effective rules, confidence and support criteria were used. In general, rules should be selected whose confidence and support values are higher than the threshold set by the user (12). In this study, despite setting a threshold limit of 50% for confidence, rules with more than 90% confidence were introduced. Also, according to the rules obtained in this study, the most effective attributes in the mortality of patients were extracted. These attributes included ISS, being an adult or a child, vital signs, falls, and arrival time. These rules indicate the existence of a significant relationship between the ISS and the patient's survival, regardless of clinical symptoms and whether the patient is an adult or a child so that if the patient's ISS is classified as minor or moderate, the patient will survive with 94% certainty. In this regard, Champion et al. showed that mortality and morbidity rates increase significantly with increase in TRISS (13). The relationship between ISS and mortality in trauma patients has been investigated by several studies (14, 15). These studies indicate a relationship between injury severity and mortality in trauma patients, which is similar to the findings of the present study. Age is also an important factor in the outcome of trauma patients, as mortality increases with age (16).

Also, these rules indicate the existence of a relationship between the time of the patient's transfer to a hospital and his/her survival, regardless of vital signs. The rules also showed that in road accidents or the cases of penetrating and non-penetrating (blunt) injuries, if the patient's time to reach the emergency department is less than 10 minutes, regardless of the vital signs, the patient will survive with 97% certainty. A study of the transfer time to the center for patients with acute traumatic subdural hemorrhage showed that those who arrived quickly from the site of injury to a designated trauma center were more likely to survive (17). Various studies have shown that reducing the time between injury and definitive treatment improves outcome and is known as the "golden time" in trauma (18, 19). In one of the rules, it was also stated that if the cause of the trauma is a fall and the vital signs are abnormal, the person will survive with 98% certainty. Another rule also showed that if the patient's ISS is minor, the vital signs are normal, and the person is an adult, even if the time to reach the emergency department is more than 10 minutes, the patient will survive with 99% certainty. These rules should be interpreted considering that the data of the registries used in this dataset were extracted from the most advanced trauma centers in Iran, in which specialized services are provided by experienced specialists. For this reason, the cases leading to death in the field of falls and other areas of trauma are less common in these centers. Meanwhile, it is necessary to note that these results cannot be generalized to all trauma patients, because a percentage of patients died at the scene and were not transferred to the emergency department at all, so their information is not available in the dataset.

Pre-hospital communication, transport system, trained personnel, and qualified trauma care personnel are all of great importance for the success of a trauma system (20). Therefore, in general, it seems that in terms of human resources and diagnostic and treatment modalities, if patients are transferred to trauma centers as soon as possible, the probability of their survival would be very high. For this reason, pre-hospital emergency medical services (EMS) needs to be carefully examined to adopt new technologies, techniques, and tools to improve these systems, if necessary, which may in turn lead to improved quality of care in trauma patients (21). Pre-hospital trauma care has a direct impact on survival. This system should ensure rapid access and dispatch of qualified personnel, appropriate on-scene care, and safe and rapid transfer of the patient to the nearest and most appropriate facility. The primary focus is on training paramedics to provide basic resuscitation, triage, and treatment for trauma patients. Effective pre-hospital care requires coordination between various public safety agencies and hospitals to maximize efficiency, minimize duplicate services, and provide care at a reasonable cost (20). It is also suggested to pay attention to the improvement of the trauma transportation system and transportation times for severe trauma patients. Several studies have shown that increase in the transportation time of trauma patients leads to increased mortality (22). As a result, complications due to long transportation and insufficient resuscitation can be predicted and a higher level of care can be considered for these patients. Also, since studies show that for severe trauma patients with ISS >12, air transportation is more effective than ground transportation (23), it is better to pay more attention to air transportation for these patients and improve the care for the area of trauma.

5. Limitation

Among the limitations of this research, we can mention the imbalance of the dataset, so that the number of data of deceased people is almost 2% of the dataset, and 98% of the data were related to survived patients. In order for a provincial center to be included in the National Trauma Registry of

Iran, a minimum requirement of human resources, equipment, and level of health care service are considered by the Strategic Council held annually. Moreover, this paper used bootstrap sampling technique to avoid the imbalance as much as possible.

6. Conclusion

In road traffic accidents, if the ISS is minor or moderate and the vital signs are normal, the person will survive with 98% certainty, and if the vital signs are abnormal, the person will survive with 92% certainty. If ISS is minor in penetrating trauma, regardless of vital signs and if the patient is transported in less than ten minutes, the person will survive with 98% certainty. Also, if the ISS is minor in Non-penetrating trauma, regardless of vital signs and if the patient is transported in less than ten minutes, the person will survive with 99% certainty. As a result, complications due to long transportation and insufficient resuscitation can be predicted and a higher level of care can be considered for these patients. If the patient is tagged as ISS-minor, the vital signs are normal and the person is an adult, even if the time to reach the emergency department is more than 10 minutes, the patient will survive with 99% certainty. If the person is an adult, has Non-penetrating (blunt) injuries, the vital signs are normal, and the patient reaches the destination in less than or equal to 10 minutes, the person will survive with 99% certainty.

7. Declarations

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7.2. Author contributions

The authors confirm contribution to the paper as follows: study conception and design: M.S, M.N.I; data collection: N.A.F, M.N.I; analysis and interpretation of results: M.S, M.N.I., H.B, N.T; draft manuscript preparation: M.S. All authors reviewed the results and approved the final version of the manuscript.

7.3. Ethical Permission

This article does not contain any studies with human participants or animals. Ethical Code: IR.MUI.NUREMA.REC.1400.044

7.4. Informed consent

Not applicable.

7.5. Conflicting interests

Authors declare that they have no conflict of interest

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