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Original Article

Internal Medicine Section

Using an Artificial Neural Networks (ANNs) Model for Prediction of Intensive Care Unit (ICU) Outcome and Length of Stay at Hospital in Traumatic Patients

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ABSTRACT

Introduction: Currently applications of artificial neural network (ANN) models in outcome predicting of patients have made considerable strides in clinical medicine. This project aims to use a neural network for predicting survival and length of stay of patients in the ward and the intensive care unit (ICU) of trauma patients and to obtain predictive power of the current method.

Materials and Methods: We used Neuro-Solution software (NS), a leading-edge neural network software for data mining to create highly accurate and predictive models using advanced preprocessing techniques, intelligent automated neural network topology through cutting-edge distributed computing. This ANN model was used based on back-propagation, feed forward, and fed by Trauma and injury severity score (TRISS) components, biochemical findings, risk factors and outcome of 95 patients. In the next step a trained ANN was used to predict outcome, ICU and ward length of stay for 30 test group patients by processing primary data.

Results: The sensitivity and specificity of an ANN for predicting the outcome of traumatic patients in this study calculated 75% and 96.26%, respectively. 93.33% of outcome predictions obtained by ANN were correct. In 3.33% of predictions, results of ANN were optimistic and 3.33% of cases predicted ANN results were worse than the actual outcome of patients. Neither difference in average length of stay in the ward and ICU with predicted ANN results, were statistically significant. Correlation coefficient of two variables of ANN prediction and actual length of stay in hospital was equal to 0.643.

Conclusion: Using ANN model based on clinical and biochemical variables in patients with moderate to severe traumatic injury, resulted in satisfactory outcome prediction when applied to a test set.

Keywords: Information technology, Diagnostic value, Trauma

INTRODUCTION

Trauma centers must have a comprehensive report on the status and progress of daily operations for trauma victims, and also continually compare the final results of care provided in the centre with an international standard. According to USA's National Vital Statistics Reports 2001, nearly 115,200 deaths occur each year due to traumatic injuries and many patients who survive, suffer from lifetime disabilities [1]. Considering the high rate of trauma patients, predicting outcome and possible consequences of the expansion and improvement of health care in such patients will be helpful. Meanwhile, due to the limitations of our understanding of the pathophysiology of a complex network of injuries to overcome the limitations of traditional methods, integrating clinical decision-making with computer science seems necessary [2].

Revised Trauma Score (RTs) and Injury Severity Score (ISS) are the routine scoring systems that have been used to predict the outcome in trauma patients. The RTS is a scoring system based on defined intervals of Glasgow Coma Scale (GCS), SBP, RR,, in which value from 0 to 4 as assigned to each interval. ISS is calculated based on the anatomic location of the lesion formed and the sum of squared scores (Abbreviated Injury Scale) [3]. Another scoring system that increasingly has used in recent years is the TRISS, which estimates a probability of survival for each patient based on trauma score, ISS, and age [4]. It has been reported that TRISS has equal or superior capability in the prognosis of traumatic patients compared to the traditional and ICU scoring systems such as Acute Physiology and Chronic Health Evaluation (APACHE II) [5,6]. Unfortunately, despite all the advantages, TRISS is unable to predict a poor outcome ensued by poor provided care [7], needs biochemical parameters of associated chronic diseases [8], and is unable to provide an estimate of the likely time of death or discharge or probable length of ICU or hospital stay and accordingly the hospital costs [9].

Some researchers even preferred the device-based prediction (International classification of diseases) ICD-9 to TRISS, especially if the system is based on intelligent networks such as ANN [10]. But basically use of systems based on ICD-9 is very time consuming; therefore, applying ANN-based systems fed by physiological factors may significantly improve trauma decision making.

ANNs are computational or information processing models that are inspired by biological neural systems, such as brain. ANN is configured and adjusted for certain applications such as pattern recognition or data classification, through a learning process, similar to biological systems [11-13]. Formerly, in a study and after training a prototype ANN was described and succeeded in diagnosing sepsis in blunt trauma victims [14].

Therefore, this study aimed to use an ANN for predicting survival and length of stay of patients in the hospital and ICU of trauma patients and to obtain predictive values of the current method.

MATERIALS AND METHODS

Study Design and Population

All trauma patients admitted to the emergency ward of Tabriz health centers from October 2006 to October 2009, was studied. This study was approved by the ethics committee of Tabriz University of Medical Sciences and all participants signed the informed consent.

Patients who were treated as outpatients and patients with non-traumatic and fatal injuries were excluded.

Data Collection

Data, including mechanism of trauma, the site involved, such as head and neck, facial, chest, abdominal and pelvic, extremities, damage to the skin was collected. Vital signs and physical examination of patients in the emergency department, including GCS, SBP, respiratory rate (RR), age, injury form also were collected. Laboratory findings consisted of hemoglobin (Hb), oxygen saturation, blood glucose, blood potassium, urea, creatinine, and medical history, were recorded.

Methods

Totally, data from 125 trauma patients admitted to the emergency, including their follow-up of hospitalization duration were used in this study which is explained below.

As discussed about any ANN, NS requires sufficient number of fact-result pairs to learn. Therefore, we started to feed the NS by the biologic data recorded from patients, paired with their outcomes (including their survival and length of stay in hospital/ ICU), one by one. NS manual explains how the training can be stopped when the NS learning curve levels off close to zero (this dynamic curve appears on a window in the program). After inputting the data of the 95th patient, we found that the learning curve of NS properly leveled off. As suggested in the manual, this trained NS was now ready to be tested. For group testing stage, trained NS needs the least number of 30 new patients. Thus, data from 30 new cases were collected. Trained NS was tested on these 30 cases. Finally, predicted results of this group, were compared to their actual available outcomes. TRISS probability of survival of the patients and ISS and RTS components, were calculated as well. We used a licensed Neuro-Solution version 5 (Neuro-Dimension, Inc. Neuro-Solutions Getting Started Manual Version 5). In brief, this software combines a modular, icon based network design interface. It is also a very typical model of Multi-Layer Perception (MLP), which is commonly used in developing ANNs and solving the problem. In this study, an ANN composed of three layers was used. This ANN was trained using the information obtained from victims and then predicted the survival, length of hospitalization and ICU stay, for 30 trauma patients. Then, the obtained sensitivity and specificity were compared with the actual results from these patient's follow-up.

STATISTICAL ANALYSIS

Data collected from the patients, were recorded in statistical software SPSS 16. The predictive power of TRISS was assessed using ROC curves and area under the curve was taken for the standard TRISS. A chi-square test was used to compare the predicted results and the actual results of the outcomes. To determine the strength of the adopted ANN prediction, hospital and ICU length of stay, paired t-test and Pearson correlation coefficient, was used. p<0.05 was considered as statistically significant level.

RESULTS

One hundred and twenty five trauma patients with mean age of 35.36 ± 19.16 (age range of 1-84) years were evaluated. In terms of gender distribution 30 (24%) and 95 (76%) of patients were females and males, respectively. The most predominant type of trauma was facial injury with the frequency of 76 (60.8%) [Table/Fig-1].

In terms of forms of injury, 5(4%), 118 (94.4%) and 2 (1.6%) of the cases were presented as penetrating, blunt, simultaneous penetrating and blunt trauma respectively. Of the 125 patients, 20 (16%) patients died during hospitalization and 105 (84%) were discharged after hospitalization or ICU. There was a significant difference between 'survived' and 'dead' groups in term of Spo2 (p=0.002) and GCS (p<0.001) mean values [Table/Fig-2].

Type of trauma	Overall No. (%)	Survived No. (%)	Dead No. (%)
Head and neck trauma	66 (53.8)	51 (48.57)	15 (75)
Facial trauma	76 (60.8)	61 (58.09)	15 (75)
Chest trauma	23 (18.4)	20 (19.04)	3 (15)
Abdominal and pelvic content trauma	16 (12.8)	13 (12.38)	3 (15)
Pelvic and organ trauma	56 (44.8)	48 (45.71)	8 (40)
Dermal trauma	31 (24.8)	23 (21.90)	8 (40)

[Table/Fig-1]: Frequency and type of traumatic injuries among the included patients

Vital signs and clinical findings	Overall Mean ± SD	Survived Mean ± SD	Dead Mean ± SD	p-values
SBP	117.2 ±28.22	117.07±27.80	118.00±31.05	0.89
RR	24.83±9.67	24.87 ±9.37	24.65±11.42	0.93
PR	94.95±22.20	94.10±21.46	99.45±25.90	0.325
SPo2	92.47±6.49	93.25±5.80	88.40±8.38	0.002
GCS	12.59±3.23	13.10±2.78	9.90±4.12	<0.001

[Table/Fig-2]: Descriptive statistics related to the trauma patient's vital signs and GCS scores
Systolic blood pressure (SBP), respiratory rate (RR), pulse rate (PR), Glasgow coma score (GCS)

There was only a significant difference between blood glucose (p<0.001) and BE (p=0.02) mean values of 'survived' and 'dead' groups (p>0.001) [Table/Fig-3].

Lab findings	Overall Mean ± SD	Survived Mean ± SD	Dead Mean ± SD	p-values
BE	-4.88±4.11	-6.8±5.81	-4.50±3.62	0.02
Hb	13.32±2.55	13.39±2.58	12.97±2.38	0.49
BG	162.98±63.15	154.03±54.71	209.95 ±82.90	<0.001
K	4.16±0.35	4.14±0.34	4.29 ± 0.42	0.09
Bun	28.98±13.68	28.50±14.19	31.55 ±15.59	0.36
Cr	0.98± 0.27	0.93± 0.28	1.8 ±0.23	0.12

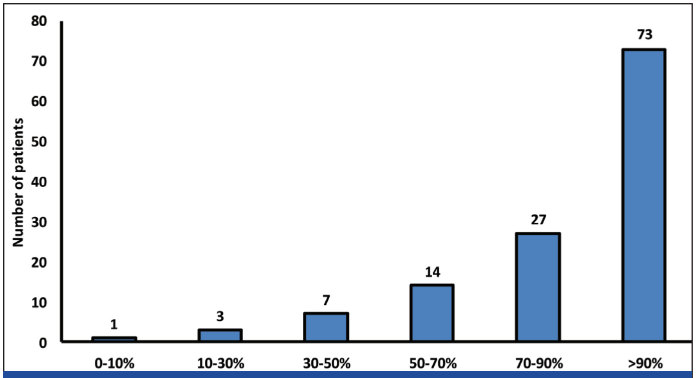
[Table/Fig-3]: Descriptive statistics related to laboratory findings of the trauma patients.
Base Excess (BE), Hemoglobin (Hb), blood glucose (BG), potassium (K), urea, creatinine (Cr)

Type of trauma	Overall No. (%)	Survived No. (%)	Dead No. (%)	P-values
Ischemic Heart Disease	7 (5.6)	6 (5.71)	1 (5)	0.68
Hypertension	12 (9.6)	10 (9.52)	2 (10)	0.95
Chest trauma	34 (27.2)	24 (22.85)	10 (50)	0.012
Smoking	8 (6.4)	5 (4.76)	3 (15)	0.11
Alcohol	7 (5.6)	2 (4.76)	2 (10)	0.31
Diabetes Mellitus	7 (5.6)	6 (5.71)	1 (5)	0.68

[Table/Fig-4]: Co morbidity Frequency table of trauma patients

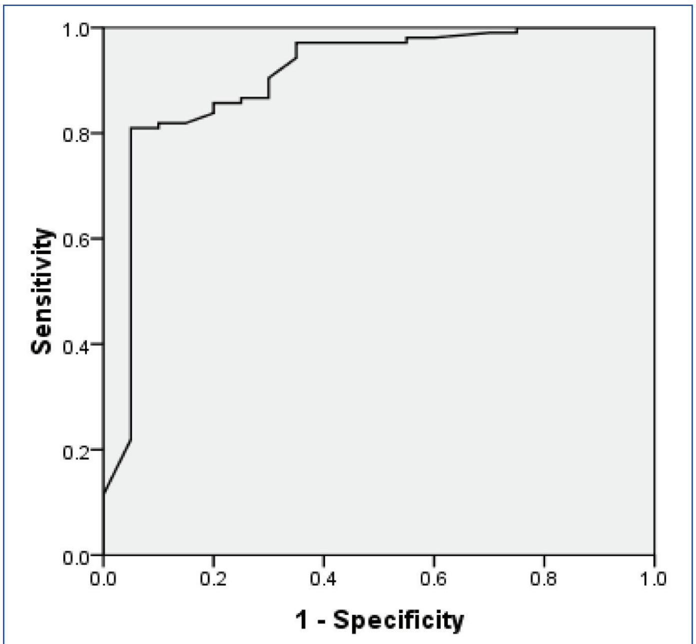
There was no significant difference between mean age of survived and dead groups (34.48 82 vs. 40 20.74. p=0.24). The mean TRISS criteria for the cases were 83.53% ±19.73. The lowest calculated probability of survival was 3.20% for the patients died during hospitalization, and the highest rate was 99.60% for the patients who were discharged after recovery Co-morbidities didn't have statistically any significant effect on outcomes [Table/Fig-4].

Overall 73 (52.4%) patients were over 90% fortress criteria and only 11 (8.8%) patients had TIRSS measureless than 50% [Table/Fig-5]. There was a statistically significant difference between mean TRISS predicted values of recovered patients compared to the dead cases (89.13 ± 11.86 vs. 54.15 ± 26.24, p<0.001).



[Table/Fig-5]: The number of trauma patients in the standard TRISS predicted probability of survival

[Table/Fig-6] ROC curve of the TRISS results. Area under the curve in the diagram is equal to 0.905 and the standard error was equal to 0.043.



[Table/Fig-6]: ROC Curve
Diagonal segments are produced by

The TRISS value calculated at a higher rate of probability of survival of 84.2%, showed a sensitivity of 81% and a specificity of 95% in predicting probability of survival [Table/Fig-6]. From 30 patients, three died and 27 survived. ANN had predicted two deaths out of these three cases, and 26 survived patients out of 27 cases [Table/Fig-7].

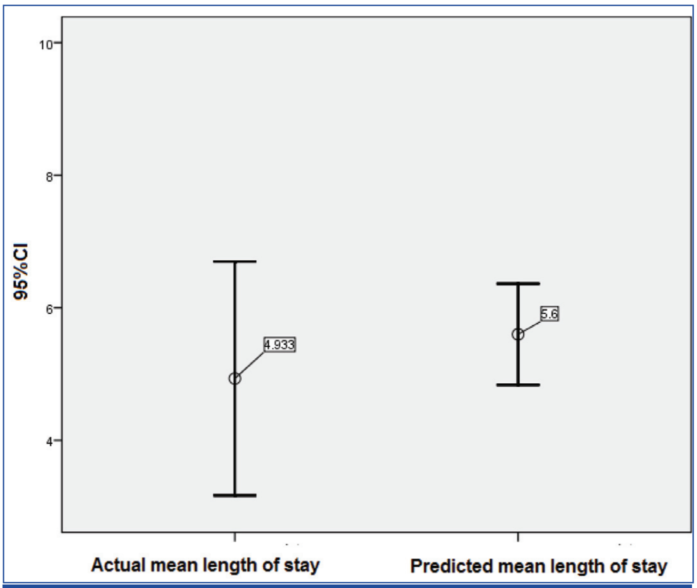
Sensitivity and specificity of ANN in predicting the outcomes of trauma patients were 75% and 96.2%, respectively. The positive predictive and negative predictive values were 75% and 96.26%, respectively [Table/Fig-7]. Comparing the results between those obtained by the ANN and the real outcome of trauma patients, indicated a statistically significant difference (p=0.2).

In the group assessed by the ANN, the mean TRISS measure was 89.02% ± 16.78. The lowest and the highest TRISS measures were 15.50% and 99.60%, respectively. The mean TRISS measures for deceased and recovered patients were 57.56% ± 41.18 and 91.33% ± 9.69, respectively. The mean length of ICU stay in 30 patients was 5.67 ± 2.48 d; hence, the ANN predicted mean length of ICU stay was 4.93 ± 0.80 days. The differences between the two groups were not statistically significant (p=0.21) [Table/Fig-8].

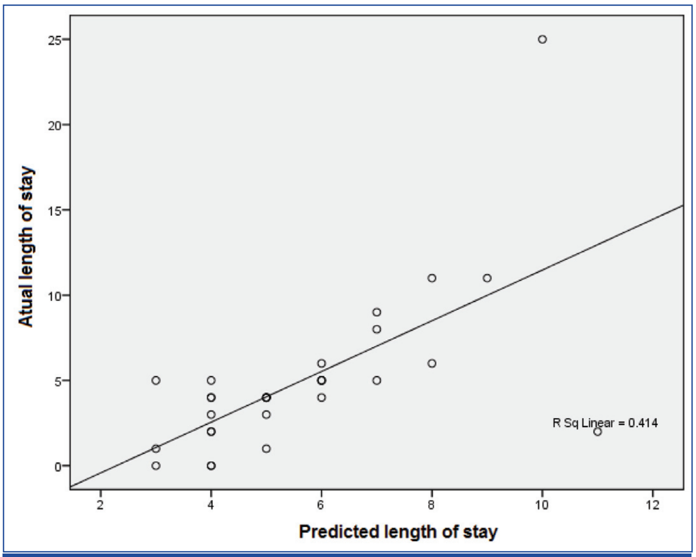
ANN vs. Actual	TP	FP	TN	FN	Sn	Sp	PPV	PPN	Acc
Values	26	1	2	1	75%	96.2%	75%	96.2%	93.3%
95%CI	---	---	---	---	12.5-98.2%	079.1 – 99.8%	12.5 - 98.2%	079.1 – 99.8%	88.2 – 99.9%

[Table/Fig-7]: ANN predicted outcome vs. actual data of trauma patients
TP, true positive; FP, false positive; TN, true negative; FN, false negative; Sn, sensitivity; Sp, specificity; PPV, positive predictive value; NPV, negative predictive value; Acc, accuracy

The correlation between actual and ANN predicted length of ward stay was positive (r = 0.643) [Table/Fig-9].The difference between actual and ANN predicted mean length of stay in ICU was not statistically significant [Table/Fig-10].



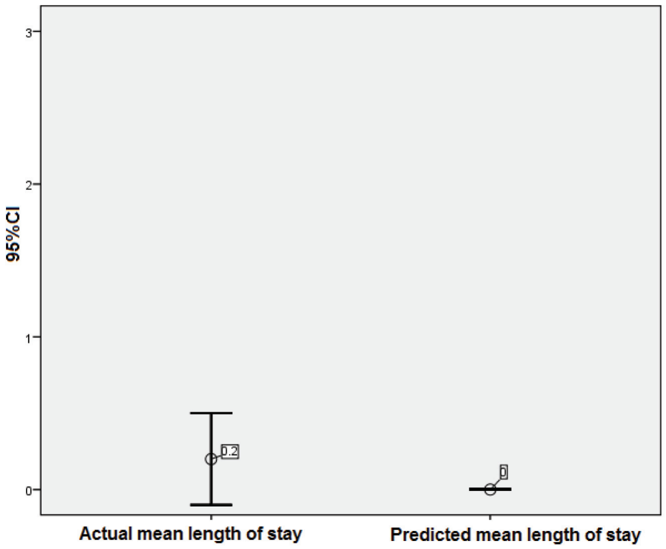
[Table/Fig-8]: The mean predicted vs. actual length of stay in the ward



[Table/Fig-9]: The scatter plot of the predicted length of stay using ANN

DISCUSSION

In recent years, the ANN-based disease outcome prediction models are developing in various health research centers, and the turnover of the t0rauma centers is widely evaluated based on the used models for predicting the probability of survival, mortality, and unexpected survival as well. Although the TRISS modeling method, a logistic regression modeling approach, is still considered as the



[Table/Fig-10]: Actual and ANN predicted length of stay in the ICU

standard method, evidence suggests that ANN based models appear even more practicable in specific circumstances. TRISS has been composed based on United States National Trauma Registries (NTRs); thus, though predicted outcomes are accurate, this scoring system may not easily be applied to all trauma care systems out of US. A single trauma patient from a developing country may show very different outcomes from that predicted by TRISS, due to local human, equipment, or even organizational constraints. To overcome these constraints, such communities should either customize the scoring systems, using their local trauma registries or rely on computerized forecasting models, such as ANN. ANN has the advantages such as trainability by quite inadequate number of cases required for trauma scoring system.

After a traumatic injury based on the specific causes that needs defining therapeutic procedures the mortality effects and long term disabilities can be minimized through decreasing the irrational decisions and thus making more accurate decisions. In addition, it seems that such a comprehensive trauma system with an emphasis on the use of resources and computer tools to assist decision making may considerably reduce the cost of the care of the patients with trauma.

Fuller et al., assessed the probability of survival by an ANN model compared with the standard TRISS, where the results of ANN in forecasting mortality rate were superior to TRISS [15]. Hunter et al., examined the details of the system to predict the results of the in vitro fertilization process to discuss and argue the generalization performance of ANNs used in such a scenario only need to be measured by k-fold cross-validation tests. They also claimed the scoring schemes can be accurately improved with such a collection of the output of several predictions [16].

Hsu et al., conducted a study to predict the outcome of patients with moderate and severe traumatic head brain in five levels of GCS using an ANN model, and reported that 75.8% of the predictions were correct, 14.6% were pessimistic, and 9.6% optimistic. The prediction performance of death and a good recovery was best and the vegetative state was worst. They suggested the ANN model may help the neurosurgeon to predict outcome after traumatic brain injury [17]. Eftekhar et al., compared the logistic regression and ANN models, in predicting the mortality rate among patients with head trauma based on the clinical findings paid. In this study, ANN system was significantly more efficient than the regression model in both fields of discrimination and calibration but showed less accuracy [18].

Di-Russo et al., developed a feed-forward back-propagation ANN using standard pre-hospital variables, emergency room admission variables, and ISS, in which the ANN showed good clustering of the data, with good separation of death and survived patients. They showed that an ANN model for predicting trauma deaths can be applied across hospitals with excellent results [19]. Similarly, Fuller et al., assessed the probability of survival by an ANN model compared with the standard TRISS, where the results of ANN in forecasting mortality rate were superior to TRISS [16]. Pearl et al., also used an ANN model to predict survival of trauma patients based on physiological, measured, and standard variables. They claimed that ANN resulted in good mortality prediction, but its performance was too sensitive and requires refinement [20]. In a similar study, Abouzari et al., predicted outcome in patients with chronic subdural hematoma using ANN and logistic regression models, and reported the ANN model is clearly superior to the logistic regression model [21].

In another study, Dickerson et al., compared the conventional multivariate regression and a feeding-forward, back-propagation, supervised ANN model for estimating urea nitrogen appearance (UNA) in multiple-trauma patients who required specialized nutrition support. They showed that use of an ANN model may be higher than conventional regression modeling techniques [22]. Despite the results of previous studies, Wolfe et al., compared three methods of developing prediction models, including logistic regression, classification trees, and ANNs in patients with trauma to administrate ICU, and showed that none of these models was optimal [23].

Recently, Shi et al., validated the use of the ANN model for predicting in-hospital mortality after traumatic brain injury surgery and compared the predictive accuracy of this model with the logistic regression model. They stated the continued use of ANNs for predictive modeling of neurosurgery outcomes is feasible [24].

As in previous studies that predict survived and long-term outcome in patients with head trauma, the use of ANNs has achieved successful results recently; our results indicate favourable performance of the ANN model.

However, despite the small sample size of our study, the combined use of clinical and laboratory data could lead to the achievement of an acceptable and specific ANN model to predict survival and case-fatality ratio for any individual trauma patient.

CONCLUSION

We believe, as the trauma registry number rises, using ANN models may help in predicting not only the survival, but also the *hospital length* of *stay*. In countries with different levels of care than developed ones, physicians in charge can have a highly specific prediction of survival, once a trauma patient enters their center. This goal may be achieved by using the available ANN models after being trained with data of even a limited number of patients. Our achievements, alongside others findings about ANN, show that these models have the potential of becoming a predictive tool in the near future.

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