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Comparison of artificial neural network and logistic regression models for prediction of outcomes in trauma patients: A systematic review and meta-analysis

Soheil Hassanipour[a], Haleh Ghaem[b,*], Morteza Arab-Zozani[c], Mozhgan Seif[d], Mohammad Fararouei[d], Elham Abdzadeh[e], Golnar Sabetian[f], Shahram Paydar[g]

[a] Student Research Committee, Shiraz University of Medical Sciences, Shiraz, Iran
[b] Research Center for Health Sciences, Institute of Health, Epidemiology Department, School of Health, Shiraz University of Medical Sciences, Shiraz, Iran
[c] Iranian Center of Excellence in Health Management, School of Management and Medical Informatics, Tabriz University of Medical Sciences, Tabriz, Iran
[d] Department of Epidemiology, School of Health, Shiraz University of Medical Sciences, Shiraz, Iran
[e] Department of Biology, Faculty of Science, University of Guilan, Rasht, Iran
[f] Anesthesiology and Critical Care Research Center, Shiraz University of Medical Sciences, Shiraz, Iran
[g] Trauma Research Center, Shahid Rajaee (Emtiaz) Trauma Hospital, Shiraz University of Medical Sciences, Shiraz, Iran

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A B S T R A C T

Background: Currently, two models of artificial neural network (ANN) and logistic regression (LR) are known as models that extensively used in medical sciences. The aim of this study was to compare the ANN and LR models in prediction of Health-related outcomes in traumatic patients using a systematic review.
Methods: The study was planned and conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) checklist. A literature search of published studies was conducted using PubMed, Embase, Web of knowledge, Scopus, and Google Scholar in May 2018. Joanna Briggs Institute (JBI) checklists was used for assessing the quality of the included articles.
Results: The literature searches yielded 326 potentially relevant studies from the primary searches. Overall, the review included 10 unique studies. The results of this study showed that the area under curve (AUC) for the ANN was 0.91, (95% CI 0.89–0.83) and 0.89, (95% CI 0.87–90) for the LR in random effect model. The accuracy rate for ANN and LR in random effect models were 90.5, (95% CI, 87.6–94.2) and 83.2, (95% CI 75.1–91.2), respectively.
Conclusion: The results of our study showed that ANN has better performance than LR in predicting the terminal outcomes of traumatic patients in both the AUC and accuracy rate. Using an ANN to predict the final implications of trauma patients can provide more accurate clinical decisions.

Contents

* Corresponding author at: Department of Epidemiology, School of Health, Shiraz University of Medical Sciences, Shiraz, Iran.
E-mail address: ghaemh@sums.ac.ir (H. Ghaem).

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Introduction

Machine learning (ML) methods are used as a powerful tool for inspecting complicated relationships [1]. Since the early 1950s these methods have been used in medical science and played an impartible role in this area [2]. Artificial Neural Network (ANN) is one of the main methods used in ML [3].

ANNs are new computational methods for machine learning, knowledge representation, and apply the knowledge gained to predict outbound responses from complex systems. This network consists of three layers of input, output and process. Each layer contains a group of neurons that are commonly associated with all other neurons in other layers [4,5].

Various other models are also used to predict health-related outcomes and one of the most commonly used models is logistic regression (LR) [6]. Classical methods, including logistic regression, have a number of assumptions and limitations for modeling relations between variables [7]. Some limitations of classical methods include considering a default distribution such as the normal distribution for response variables, the linearity of the proposed relationship, similarity and the variance of error [8]. In practice, if the actual data do not have the assumed conditions, the use of these methods is not possible or is accompanied by a significant error [9].

ANNs have eliminated most of the problems with classical statistical methods and does not require the assumptions such as normal distribution of data, the type of relationship between the independent and dependent variables, and it has itself discovered a functional relationship that this relationship may not necessarily be linear [10]. Another benefit of the ANNs is that they are processed implicitly. Therefore, if some of the cells in the network are deleted or have a false function, then there is still a chance to get the correct answer [11]. In addition, the generalizability of the neural network allows the model to provide an appropriate response to a new, untrained learning experience [11,12].

Trauma or severe injuries is defined as a mechanical damage to the body caused by an external force [13,14]. According to statistics, trauma is the sixth leading cause of death in the world [15]. Trauma and accidents are recognized as the first cause of death and disability among people less than 35 years old [16,17]. Given their characteristics, traumatic patients need the best prediction for specific services [18]. Few studies have been conducted to predict the likelihood of death, length of stay (LOS) in the intensive care unit (ICU) and other health-related outcomes using the ANN model and compare it with the LR model [19–21]. In most of these studies, several indices have been used to evaluate the performance of two models, such as the area under a curve, accuracy rate and Hosmer-Lamshow test.

Several review articles have addressed the methods of ML in burned patients and neurosurgery patients [22,23]. Often, these studies have described a variety of ML methods and did not provide comparisons about the performance of different models. Considering the necessity of a comprehensive study on common prediction methods in patients with trauma and comparing the performance of different models in this field, the aim of this study was to compare the ANN and LR models in prediction of Health-related outcomes in traumatic patients using a systematic review.

Methods

The study was planned and conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) checklist [24] in 2018

Search strategy of systematic reviews

A literature search of published studies was conducted using PubMed, Embase, Web of knowledge, Scopus, and Google Scholar in May 2018. No time duration limitation was considered. The keywords included: “Trauma”, “Wounds and Injuries”, “Artificial Intelligence” “Artificial neural network”, “Logistic Models” and “Logistic regression”. The records were then imported into EndNote X7 software (Thomson Reuters, Carlsbad, CA, USA). Thereafter, the studies were checked out based on title, abstract and full-text by two reviewers independently.

Inclusion and exclusion criteria

Articles that compared two models of ANN and LR and also were done explicitly on trauma patients were included. Articles were excluded if they did not report our desired data, which were in non-English language, and also articles that did not have access to their full text.

Data item and data extraction

The extraction form was piloted in 10 articles and subsequently revised and finalized by consensus between researchers. The extraction form included: the author names, the year of publication, the country where the study was conducted, the study population, the average age of the participants, the gender type, the outcome, the sample size, as well as the number of variables in each layers of the neural network (Input, Hidden, and Output).

Quality assessment

We used the Joanna Briggs Institute (JBI) checklists for assessing the quality of the included articles. Two reviewers independently appraised the quality of the included studies and discrepancies resolved by consensus. The results of Quality assessment presented in Table 1.

Table 1
JBI critical appraisal checklist applied for included studies.

Author name/Year	Were the two groups similar and recruited from the same population?	Were the exposures measured similarly to assign people to both exposed and unexposed groups?	Was the exposure measured in a valid and reliable way?	Were the confounding factors identified?	Were strategies to deal with confounding factors stated?	Were the groups/ participants free of the outcome at the start of the study (or at the moment of exposure)?	Were the outcomes measured in a valid and reliable way?	Was the follow up time reported and sufficient to be long enough for outcomes to occur?	Was follow up complete, and if not, were the reasons to loss to follow up described and explored?	Were strategies to address incomplete follow up utilized?	Was appropriate statistical analysis used?
Lang, 1997	Yes	Yes	Yes	Yes	Yes	Unclear	Yes	Not applicable	Unclear	No	Yes
DiRusso, 2002	Yes	Yes	Yes	Unclear	Yes	Unclear	Yes	Not applicable	NO	No	Yes
Eftekhar, 2004	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unclear	Unclear	No	Yes
Ottenbacher, 2004	Yes	No	NO	Unclear	Yes	Yes	No	No	No	No	Yes
Abouzari, 2009	Yes	Yes	NO	Unclear	Yes	Yes	No	Unclear	Unclear	No	Yes
Lin, 2010	Yes	Yes	Yes	Yes	Unclear	Yes	Yes	No	No	Yes	Yes
Rughani, 2010	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unclear	Unclear	No	Yes
Shi, 2013	Yes	Yes	NO	Yes	Yes	Yes	Yes	Unclear	Unclear	No	Yes
Stylianou, 2015	Yes	Yes	Unclear	Yes	Yes	Yes	Yes	Not applicable	Not applicable	Yes	Yes
Belliveau, 2016	Yes	Yes	Unclear	Yes	Unclear	Yes	Yes	Not applicable	Not applicable	Yes	Yes

Statistical analysis

All the analysis were conducted using STATA software, version 12 (Stata Corp LP, College Station, TX, USA) and Comprehensive met-analysis (CMA) version 2. Statistical heterogeneity was assessed by Cochran's Q statistic (with a significance level of $p \leq 0.1$) and I^2 statistic (with a significance level of $\geq 50\%$). In the presence of significant heterogeneity among the studies, the Meta-analysis was done by random effect model (with inverse variance method). The method used in this study was the calculated Odds ratio (OR) index to better understand the readers of the paper.CMA software has the ability to combine different indices together and to combine the effect of sample size and the difference of the index being compared. We concluded that the OR index can well illustrate the difference between the two models.

Risk of bias across studies

Random effect model was used for minimizing risk of bias across the studies [20,21].

Results

Description of literature search

The literature searches yielded 326 potentially relevant studies from the primary searches. 242 studies remained after removal of the duplicates. In total, 29 studies met inclusion criteria and entered into the second stage of evaluation. Some studies were excluded for the following reasons: being irrelevant to the topic (n = 204), incorrect study population (n = 23), and insufficient data (n = 5). Overall, the review included 10 unique studies. The search process and Study selection base on PRISMA flow chart in this systematic review has been outlined in Fig. 1.

Description of the included studies

According to the geographical area, five studies were conducted in USA [25–29], two in Iran [30,31], one UK [32], one China [33], and one in Taiwan [34]. According to the population of patients, four studies in head injuries, one in Pediatric Trauma Patients, one in Hip Fracture, one in Chronic subdural hematoma, one in elderly patients, one in burn injury and finally one in Traumatic Spinal Cord Injury. The basic characteristics of the included studies have been summarized in Table 2.

The results of meta-analysis

The results of this study showed that the AUC for the ANN was 0.91, (95% CI 0.89–0.83) in random effect model and 0.97, (95% CI 0.96-0.97) in fixed effect model. The AUC for LR was 0.89, (95% CI 0.87–90) in random effect model and 0.96, (95% CI 0.95.0.96) in fixed effect model. The results of the heterogeneity showed that there is a high level of heterogeneity between the studies (Q = 1256.4, df = 9, I^2 = 99.3%, $p < 0.001$ and Q= 2413.5, df =9, I^2 = 99.6%, $p < 0.001$ for ANN and LR, respectively). The result has been shown in Supplementary files 1and 2.

Another statistic that examined the performance index was the accuracy rate. The accuracy rate for ANN and LR in random effect models were 90.5, (95% CI, 87.6–94.2) and 83.2, (95% CI 75.1–91.2), respectively. The results of the heterogeneity showed that there is a high level of heterogeneity between the studies (Q = 656.5, df = 5, I^2 = 99.2%, $p < 0.001$and Q= 12,476.6, df =5, I^2 = 99.9%, $p < 0.001$ for ANN and LR, respectively). The result for accuracy rate has been shown in Supplementary files 3 and 4.

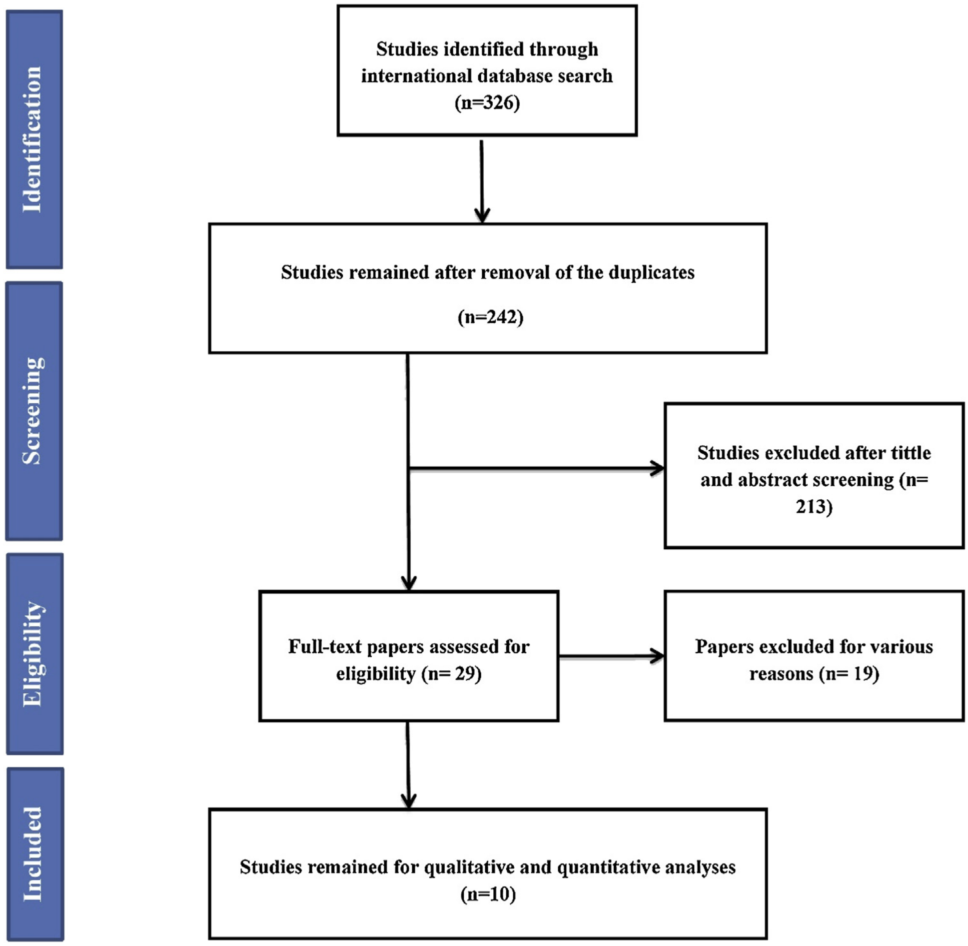

Fig. 1. Flowchart of the included eligible studies in the systematic review.

The calculated odds ratio (OR) index was used to compare two models. The results showed that the AUC for the ANN was higher than LR, which was statistically significant (OR = 1.06, 95% CI 1.01–1.10, P = 0.005, I^2 = 37%, P = 0.112).

The results of the comparison of the accuracy rate of the two models showed that the artificial neural network had a higher level of accuracy than logistic regression to predict the outcomes, which was statistically significant (OR = 1.09, 95% CI 1.00–1.20, p = 0.021, I^2 = 69.4, p = 0.006). The result for AUC and accuracy rate has been shown in Figs. 2 and 3

With regard to the Accuracy indicator, if we say the accuracy of a model is higher for identifying those who need a therapeutic action, that is, in most cases, it is well-predicted to take advantage of or not benefit from it. With regard to the AUC, when the ROC curve of the is equal to 0.05, it means, the probability is quite equal with the chance, and when model (ANN) is higher than the other (LR), that is, the model with a much higher probability can separate those who can take advantage of a remedy (true positive) from those who do not benefit an action mistakenly (false positives).

Table 2
Basic characteristics of included studies.

Order	Author	Year	Country	Population	Average age	Gender (Male %)	Application	Sample size			Neural Network Layers		
								Total	Train	Test	Input	Hidden	Output
1	Lang	1997	USA	Severe head injury	41	78	Prediction of outcome	1066	799	267	12	NR	1
2	DiRusso	2002	USA	Pediatric Trauma Patients	8.1	64	Prediction of Survival	35,385	27385	8000	13	2	1
3	Eftekhar	2004	Iran	head trauma	28.5	76	prediction of mortality	1271	839	432	23	15	1
4	Ottenbacher	2004	USA	Hip Fracture	75.5	26.3	Predicting Living Setting	3708	3015	693	13	4	1
5	Abouzari	2009	Iran	Chronic subdural hematoma	56.5	71	prediction of Chronic subdural hematoma outcome	300	150	150	8	3(1), 4 (2)	1
6	Lin	2010	Taiwan	elderly patients	80.2	32.5	predicting mortality	286	197	89	11	20	1
7	Rughani	2010	USA	head injury	39.1	72	predict mortality	7869	7769	100	11	8	1
8	Shi	2013	China	traumatic brain injury	50.8	73.5	Prediction of hospital mortality	16956	11304	5652	6	8	1
9	Stylianou	2015	UK	burn injury	21	NR	Mortality risk prediction	66611	46626	19985	15	6	1
10	Belliveau	2016	USA	Traumatic Spinal Cord Injury	41.5	80	Predict Functioning One Year After injury	3142	2362	590	3	2	1

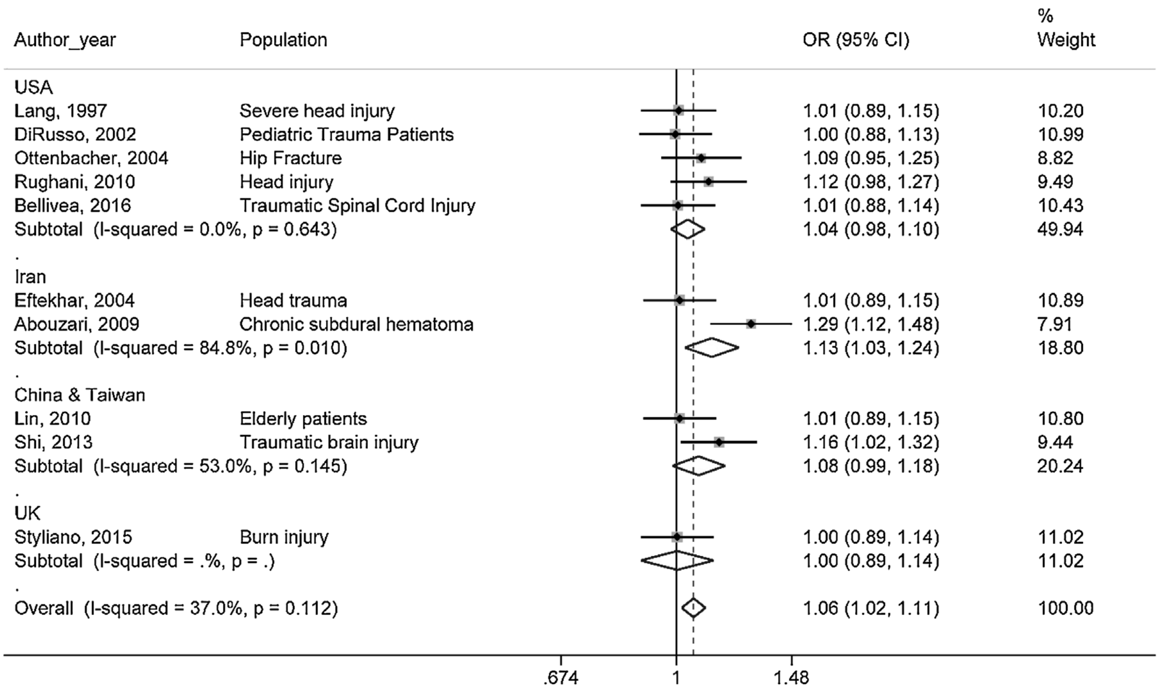

Fig. 2. Forest plot of comparison of area under a curve between Artificial Neural Network and Logistic Regression.

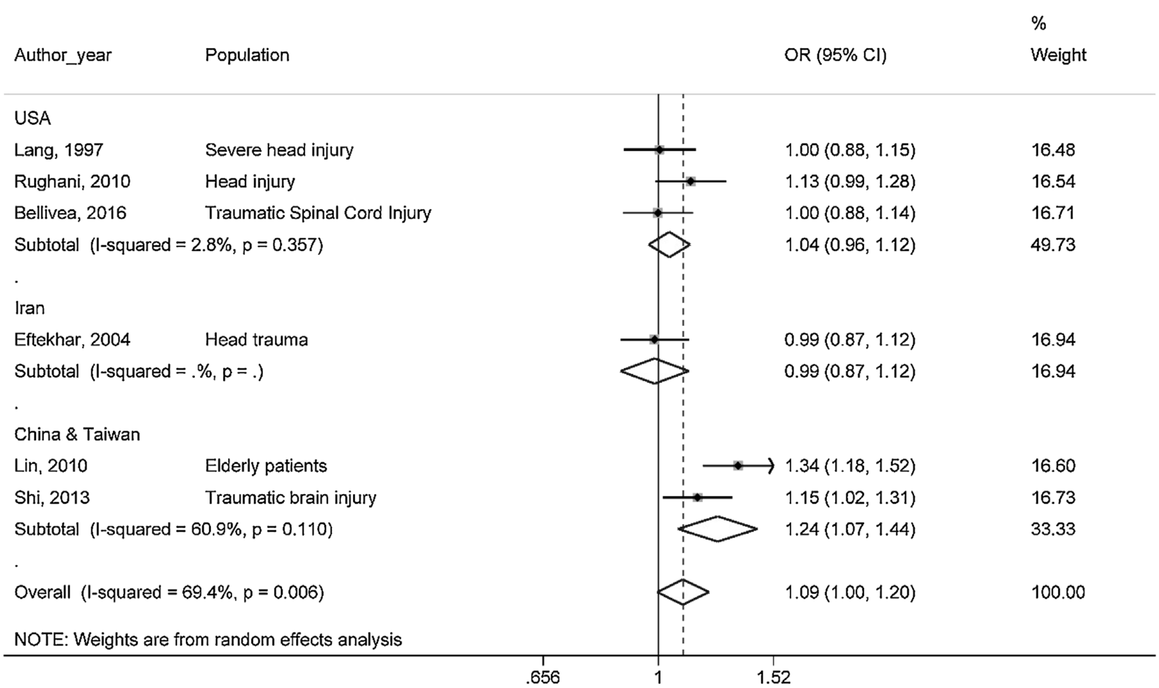

Fig. 3. Forest plot of comparison of accuracy rate between Artificial Neural Network and Logistic Regression.

The results of the Hosmer-Lamshow test also indicate the superiority of the neural network to logistic regression. Due to the small number of studies reporting this statistic between the two models, meta-analysis was not conducted. The result of performance indexes of models between studies indicated in Table 3.

Publication bias

Given that the number of articles entered in each of analyses was less than ten, investigating the publication bias was not rational [35].

Discussion

Considering the importance of the accuracy in predicting the consequences, it is important to have access to models that can make these forecasts with the highest accuracy [36]. Currently, two models of LR and ANN are known as models that extensively used in medical sciences [37]. LR is known as the most well-known model for prediction and it is easy to use, and also has easy understanding and interpretation, but it still has some limitations. LR examines linear relationships between variables and it will be difficult if there is a non-linear relationship and interconnection

Table 3
Comparison of performance indexes in Artificial Neural Network versus Logistic Regression.

Author	Outcome	Results (Performance Indexes)					
		ANN			LR		
		ROC	HLC-S	AR	ROC	HLC-S	AR
Lang	Prediction of mortality	0.848	NR	80.9	0.841	NR	80.5
DiRusso	Prediction of survival	0.961	10.5	NR	0.964	36	NR
Eftekhar	Prediction of mortality	0.964	41.51	95.09	.953	53.13	96.37
Ottenbacher	Predicting Living Setting	0.73	NR	NR	0.67	NR	NR
Abouzari	Prediction of chronic subdural hematoma outcome	0.767	NR	NR	0.594	NR	NR
Lin	Prediction of mortality	0.949	NR	98.4	0.938	NR	73.6
Rughani	Prediction of mortality	0.86	NR	87.8	0.77	NR	78
Shi	Prediction of hospital mortality	0.896	43.9	95.23	0.774	53.18	82.44
Stylianou	Mortality risk prediction	0.974	NR	NR	0.971	NR	NR
Belliveau	Predict Functioning One Year After injury	0.880	NR	87.7	0.875	NR	87.8

ANN: Artificial Neural Network; LR: Logistic Regression; ROC: Receiver Operating Characteristic; HLC-S: Hosmer-Lemeshow C statistics' AR: Accuracy Rate; NR: Not Reported.

between the variables [38,39]. On the other hand, ANN does not have the problems mentioned for LR and uses the learning methods included in the model for correcting itself and could provide much more accurate predictions that would be highly regarded by physicians and clinical decisions [11].

In the present study, two main indicators (AUC and accuracy rate) were used to predict the results of both artificial neural network models and logistic regression. Finally, the results of these two indicators were compared with the calculated OR.

The results of our study showed that the ANN model had a higher AUC than LR. According to the OR index, the ANN model has a higher prediction of about 6% than the LR. The results from other studies also indicate the superiority of ANN model to LR. Nilsoon et al., found the predicting of mortality rate after cardiac surgery has more accurate predictions by ANN [40]. In our study, the prediction made by ANN was approximately 91% similar to that of other studies in other patients. Ahmed et al., showed that about 90% of the survival of patients with colorectal cancer is predicted by the ANN [41]. Another study predicted a 5-year survival rate for breast cancer patients based on the ANN model of 93% [42].

In general, ANN has a stronger predictor of LR. One of the possible reasons is the interaction between variables does not affect the ANN [27], but if the goal is to study the causal relationship between variables, LR can be a suitable choice [43]. Nevertheless, the ANN will be more predictable, and it can be said that these two models can complement each other [44]. In situations where the ANN does not have the ability to report individual factors, LR can still provide this information [45].

The results of this study showed that the accuracy of ANN model is better than LR. Using the calculated OR index, the ANN has a higher prediction accuracy rate than LR of 10%. The reported accuracy for the ANN was higher than 90% in our study. The results of other studies were in line with our study. In a study on CSDH patients, the ANN reported a higher degree of accuracy [46]. Also, in studies of the survival of colon [47], breast [48] and Gastric cancer [49], the accuracy of the ANN was higher than 90%. Limited studies have reported the accuracy of LR higher than the ANN. Eftekhar et al., in a study on brain trauma patients showed that the accuracy of LR is slightly higher than ANN [30]. One of the possible reasons for this finding can be the comparison between only two models. It is suggested that other performance indicators should be considered in order to find the best comparator [50]. However, in mentioned study, the discrimination and calibration of ANN was higher than LR.

Strength and limitation of study

One of the most important strengths of the present study is that so far no studies have examined the two models of ANN and LR with a meta-analysis approach. The indicators used in most studies provided the ability to compare the two models in our study. The main limitation in systematic review studies, as well as the present study, are to use the results of other studies, which makes our knowledge limited to existed information on a specific issue. Another limitation of this research was the various consequences that were evaluated and limited our ability to compare our results with two models of ANN and LR. And finally, main constraints for our study is the lack of studies that compares the two models. Most studies that compared the two models of ANN and LR, was about phenomena like the survival of cancer patients and cardiovascular disease.

Recommendation

Our study can be a pioneer for other studies, and other studies that examine other outcomes can confirm our results about the superiority of ANN (a later of AI) to the LR. Given that the ANN model provides more accurately predictions for examining health-related outcomes such as death rate, survival rate and duration of hospitalization in the intensive care unit, it is suggested that, along with other classic and popular models such as LR, an ANN model should be used to make accurate and reliable decisions in patient care.

Conclusion

The results of our study showed that ANN has better performance than LR in predicting the terminal outcomes of traumatic patients in both the AUC and accuracy rate. Using an ANN to predict the final implications of trauma patients can provide more accurate clinical decisions.

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Conflict of interest statement

The author(s) declare that they have no competing interests.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.injury.2019.01.007.

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