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Use of neural network based on international classification ICD-10 in patients with head and neck injuries in Lublin Province, Poland, between 2006–2018, as a predictive value of the outcomes of injury sustained

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Abstract

Introduction and objective. Head and neck injuries are a heterogeneous group in terms of both clinical course and prognosis. For years, there have been attempts to create an ideal tool to predict the outcomes and severity of injuries. The aim of this study was evaluation of the use of selected artificial intelligence methods for outcome predictions of head and neck injuries.

Material sand Method. 6,824 consecutive cases of patients who sustained head and neck injuries, treated in hospitals in the Lublin Province between 2006–2018, whose data was provided by National Institute of Public Health / National Institute of Hygiene, were analyzed retrospectively. Patients were qualified using International Statistical Classification of Diseases and Related Health Problems (10th Revision). The multilayer perceptron (MLP) structure was utilized in numerical studies. Neural network training was achieved with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method.

Results. In the designed network, the highest classification efficiency was obtained for the group of deaths (80.7%). The average value of correct classifications for all analyzed cases was 66%. The most important variable influencing the prognosis of an injured patient was diagnosis (weight 1.929). Gender and age were variables of less significance with weight 1.08 and 1.073, respectively.

Conclusions. Designing a neural network was hindered due to the large amount of cases and linking of a large number of deaths with specific diagnosis (S06). With a predictive value of 80.7% for mortality, ANN can be a promising tool in the future; however, additional variables should be introduced into the algorithm to increase the predictive value of the network. Further studies, including other types of injuries and additional variables, are needed to introduce this method into clinical use.

Key words

head, TBI, injury, neck, mortality, Artificial Neural Network, artificial intelligence, mortality prediction, trauma scoring system, injury scoring system

INTRODUCTION

Head and neck injuries constitute a serious health and socio-economic problem worldwide [1]. According to statistical data published by the CDC, head and neck injuries account for 4–16% of all trauma hospitalizations [2, 3], and are also the cause in the USA of approx. 25% of severe life threatening injuries and disabilities [4]. They affect patients in every age group, with particular predilection in the following groups: over 75-years-old, 0 – 5, and 15 – 24-years- old [5, 6]. In the UK, brain injuries are the leading cause of death and disability among those under 40-years-old [7].

In the literature, the term Traumatic Brain Injuries (TBI) has replaced the definition of head injury in order to emphasize the essence of damage affecting such an important organ as the brain. International Classification of Diseases issue 10 (ICD-10) defines TBI as diagnosis from S00 – S19. Meta-analysis published by Peeters et al. [8] demonstrate that it is difficult to determine the frequency of head injuries which are geographically conditioned, and estimated in very wide ranges from 47.3/100,000 up to 576/100,000 inhabitants, depending on the study [8]. Mortality rate, based on the

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above-mentioned meta-analysis, was estimated at 10.3 per 100,000 cases. In the USA in 2017, 61,131 TBI-related deaths were recorded which accounted for about 2.2% of deaths in the entire population [9]. The population structure of European residents suffering from TBI have been presented by Majdan at al. [10], according to which men are more likely to suffer from this injury (61%) than women (39%); however, in the population over 65 years of age this proportion is reversed [12, 13]. Currently, head injuries affect mainly elderly patients, although they are also relatively common among young adults [5, 6]. It is noteworthy that TBI substantially contribute to total healthcare costs. The economic burden is linked with treatment, rehabilitation and loss of productivity caused by disability [14, 15]. The global cost of brain injury has been estimated at approximately 400 billion USD annually, representing 0.5% of the gross world product [7].

Head and neck injuries are a heterogeneous group of injuries, with respect to both clinical course and outcomes. A special group of injured persons are those with severe and potentially fatal injuries. For years, there have been attempts to create an ideal diagnostic tool and a system of treatment of the outcomes of injuries, which will guarantee the injured person treatment in a facility appropriate to the severity of the injury, as well as an appropriate treatment, and also allow prediction of the outcome. It would also allow the initial qualification of the patient for treatment in a reference centre, based on the severity of the injury. A significant progress in the treatment of the outcomes of injuries was the creation of the first scales for assessment of the severity of an injury. They reflect numerically the condition of the patient after the injury, taking into account damaged body regions, mechanism of the injury, age, physiological parameters and comorbidity occurrence, of which allows for directing the further diagnostic and therapeutic process and assessment of prognosis at the initial stages of treatment. Currently, there are several injury scales which are widely in use: Abbreviated Injury Scale (AIS) [16], Revised Trauma Score (RTS) [17], Injury Severity Score (ISS) [18], New Injury Severity Score (NISS) [19], Revised Trauma and Injury Severity Score (TRISS) [20] and International Classification based Injury Severity Score (ICISS) [21]. The severity of the brain injury is classified according to the GCS scale as mild, moderate or severe, where the mortality rate of the latter reaches even 40% [22, 23]. A special role is assigned to the ICISS score proposed by Osler in 1996, which is based on the International Classification of Diseases version 9 (ICD-9). Later, Osler and some other authors showed a higher predictive value of the assessment of the severity of an injury using the International Classification of Diseases over other injury scales [19, 24]. Another scoring system based on ICD-10, Life Threat Index (LTI), was proposed by Nogalski in 2008 [25] and its usefulness was proved on a group of 485 patients treated in a regional trauma centre [26]. All the available scales, however, have their disadvantages, e.g. they take into account only the most severe injuries or do not take into account physiological parameters. Other presented limitations of currently available scores are the undertriaging or incorrect classification of patient's condition as unsurvivable [27, 28]. Constantly increasing trauma visits to an Emergency Department require an appropriate scoring tool for improving treatment outcomes [29].

The use of artificial intelligence in medicine has been gaining recognition in the medical community, e.g. in radiology [30, 31] and diagnosis of selected disease entities [32–37]. It allows for rapid and precise analysis of many parameters which can potentially be used in predicting the outcomes of injuries. First studies using artificial intelligence in medicine, specifically neural networks, were published by Penny and Frost in 1996 [38], which proved that the effectiveness of the network was comparable to that of clinical decisions. The first work that referred to the use of neural networks from the assessment of patients with head trauma was that of Lang [39]. He was the first to show the effectiveness of neural networks in predicting treatment outcomes in patients with head injuries in comparison to standard logistic regression. Subsequent research groups proved the sense of using neural networks as a useful prognostic tool in post-injuries patients, both in general trauma [40–42] and brain injuries [43, 44].

In recent years some attempts have been made to use artificial intelligence to assess the prognosis of patients after trauma, based on the International Classification of Diseases. This stems from the fact that all prognostic scales known so far based on ICD are linear scales, and each individual element has the same significance and influence on the patient's survival. However, clinical practice shows that the dependencies between risk factors are not linear. Considering all of the above, the ability to train the neural network and risk stratification for individual risk factors allow using this tool in predicting prognosis in a patient after injury.

The aim of this study was to evaluate a machine learning model based on ICD-10 codes for mortality prediction among patients suffered head injuries, in the group residents of the Lublin Province in Poland between 2006–2018.

MATERIALS AND METHOD

A retrospective analysis was performed on inpatients who had sustained head and neck injuries and treated in hospitals in the Lublin Province in 2006–2018. The group was selected based on statistical data gathered by the National Institute of Public Health / National Institute of Hygiene (NIPH – PIH), obtained from hospitalization reports generated by individual hospitals. Patients were qualified for this study on the basis of the codes from the International Classification of Diseases ICD-10 in the range between S00 – S19, which correspond to head and neck injuries. ICD-10 codes T00-T14 were excluded because of their unspecified description of trauma range. A group of 143,362 patients with head trauma was selected. Furthermore, only main groups of ICD-10 diagnostic codes, without a sub-codes, were included. Cases of superficial injuries classified as S00 and S10 due to their low mortality and high number of cases, and which notably would have complicated the design of the neural network, were also excluded. Taken into account the above, a total of 20,447 cases were identified. As the study group was too large to design an ANN model, 6,824 cases were randomly picked and analyzed. The data structure of the most common cases analyzed is shown in Figure 1.

The studies conducted are preliminary analyses aimed at testing the applicability of ANN methods in analyzing the structure of hospitalizations resulting from head and neck injuries. In the analyzed case, the statistical analysis was made with Statistica 13.3 package (Tulsa, OK, USA) containing modules including machine learning and artificial neural

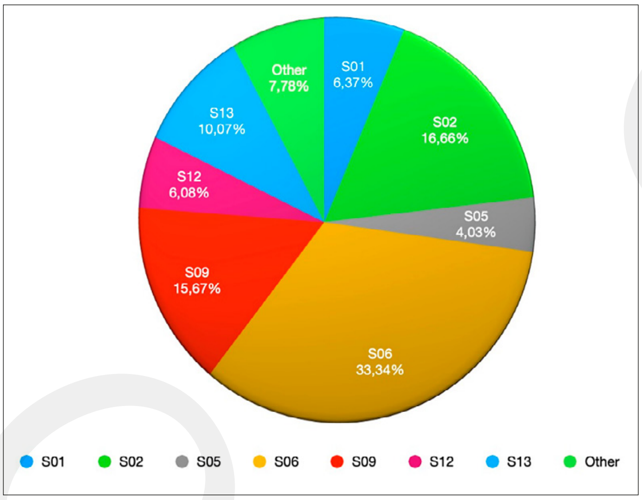


Figure 1. ICD-codes structure among selected patients

networks. For MLP network learning, 6,824 cases divided into three groups were used.

Analyzed database contained nine variables – age, gender, ICD code of injury, ICD codes of comorbidities, ICD code of injury mechanism, hospitalization unit, place of residence, and length of hospital stay. It was decided to include age, gender and the ICD-10 code of sustained injury into ANN to create a model based on simple, easy-to-gain predictors at the beginning of the therapeutic process. The input variables to the artificial neural network can be divided into qualitative and quantitative, in which the qualitative variables in the analyzed case were the diagnosis according to the ICD-10 classification (S01-S09 and S11-S19) and the patient's gender (M / F). Age was adopted as the quantitative variable. In total, 21 neurons were adopted at the input of the network.

The MLP network had nine neurons in the hidden layer. There were three possible results at the classifier output:
- discontinuation of the therapeutic process;
- referral for further treatment;
- death.

The initial variable in the analyzed regression task was the result of hospitalization. Death, treatment discontinuation, and further ambulatory treatment were adopted as possible outcomes.

Data was divided into three groups: learning (70% of cases), testing (15% of cases) and validating (15% of cases), which was connected with the learning process of the neural network. The first group was used for training the model, the second for testing and changing its parameters, and discontinuation of the therapeutic process as the final one only to check the effectiveness of the network. The allocation of cases was carried out in a random manner. The number of individual injuries was therefore distributed randomly.

RESULTS

A total of 143,362 patients were identified between 2006 – 2018 in the Lublin Province as having TBI, the majority of whom were males. Average time of hospital stay – 3,68 days; average age – 35.49 years; mortality rate – 1.52%. Demographical analysis is presented in Figure 2.

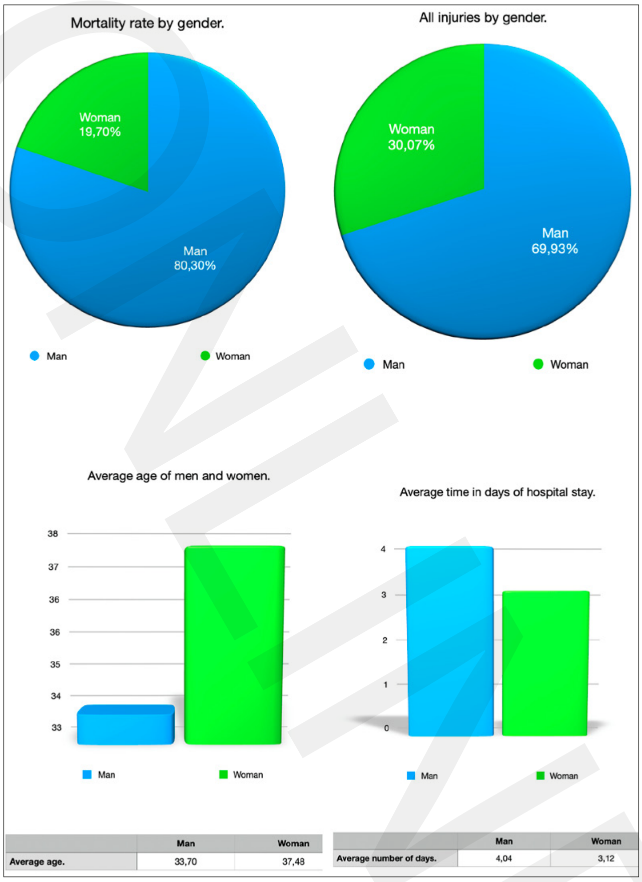


Figure 2. Demographical analysis

The structure of most common ICD recognition codes among TBI victims in the study period was analyzed (Fig. 3).

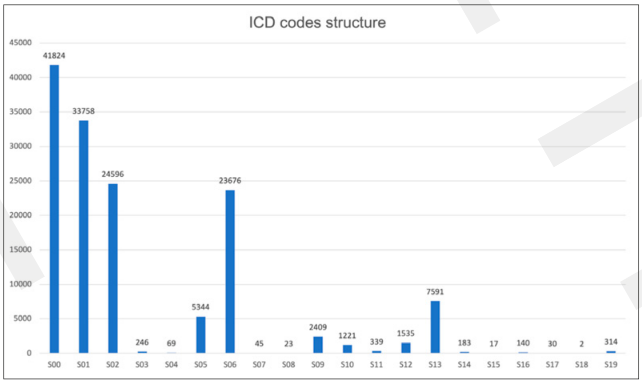
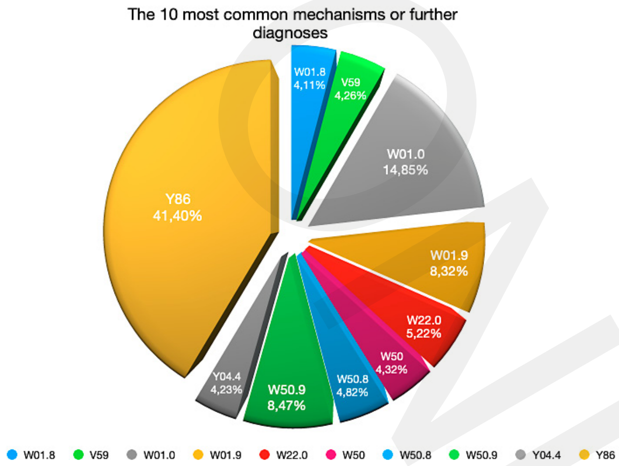


Figure 3. ICD-codes structure among whole TBI population

Injury mechanism was coded in only 62,883 (43.86%) cases, with the most common injury mechanisms codes shown in Figure 4. Records with coded mechanisms were divided into groups (Tab. 1).

Table 2 presents the quality coefficients of the neural network operation for particular sets of input data. Learning algorithm, error function and activation functions in the hidden and output layers, were also included. The training of the neural network was possible through the use of the back propagation error method. The Broyden-Fletcher-Goldfarb-Shanno (BFGS) method was used for training the neural network.



Mechanism or further diagnosis	W01.8	V59	W01.0	W01.9	W22.0	W50	W50.8	W50.9	Y04.4	Y86
Quantity	1026	1065	3708	2079	1303	1080	1 204	2 115	1056	10 339

Figure 4. 10 most common codes of injury mechanism.

Table 1. Injury mechanisms

Injury mechanism	ICD codes	N(%)
Motor vehicle accidents	V01-V99, Y85	9254 (14.72%)
Falls	W00-W09, W18	14370 (22.85%)
Falls from height	W10-W17, Y30	4172 (6.63%)
Interpersonal violence	W32-W34, W50-W52, X88-Y05, Y07-Y09, Y20, Y22-Y23	9546 (15,18%)
Self-harm	X70-X84, Y87	79 (0,12%)
Contact with animals	W53-W59, X20-X29	682 (1.08%)
Contact with machines	W24, W28-W31	262 (0,42%)
Contact with unpowered hand-tool	W20-W23, W25-W27, W44-W45, W60, Y28-Y29	6209 (9.87%)
Exposure to electricity, pressure, tempertature	W35-W41, W85-W92, X00-X19, X30-X33, Y25-Y27	56 (0.09%)
Others		18,253(29.02%)

Table 2. Quality of neural network operation

Network type	Quality (learning)	Quality (test)	Quality (validation)	Learning Algorithm	Error Function	Activation (hidden)	Activation (input)
MLP 21–9–3	66.002	64.887	65.229	BFGS 76	SOS	Tanh	Expotential

The regressive propagation algorithm defines a method of selecting neuron weights in a multilayer network using gradient optimization methods. The purpose of this algorithm is the sum of the squares differences (SOS) between the values of the network output signals and the actual values. Hyperbolic tangent function and the exponential function were adopted as the functions of neurons activation in the hidden and output layers. Table 3 contains summary of the classification of multilayer perceptron performance divided into three output groups. The number of correctly and incorrectly classified cases in each group, as well as the average value, are shown.

Table 3. Effectiveness of case classification(Network type MLP 21-9-3)

Network type MLP 21–9–3				
Case classification	Discontinuation of therapeutic process (N=2787)	Referral for further treatment (N=2508)	Death (N=1529)	Total (N=6824)
Correct	1574 (56.48%)	1696 (67.62%)	1234 (80.71%)	4504 (66.00%)
Incorrect	1213 (43.52%)	812 (32.38%)	295 (19.29%)	2320 (34.00%)

This table shows that the highest classification efficiency was achieved in the group of deaths which amounted to over 81%. The average value of outcome prediction for all analyzed cases was 66%.

Table 4 presents the sensitivity analysis of the neural network. The value of the sensitivity coefficient confirms the suitability of a given parameter for ANN learning. The greater the value, the greater the influence of the variable on the correct operation of the network. In the analyzed case diagnosis is the most important input variable. Less important variables but still impacting the correct operation of the new model are sex and age of the patient.

Table 4. Sensitivity analysis

Network type MLP 21–9–3			
	Diagnostic Code	Gender	Age
Sensitivity	1.929	1.080	1.073

DISCUSSION

Recently, the effectiveness of machine learning in mortality prediction among patients who had sustained injury, has been proved in several studies [41, 43, 45, 46], most of which were conducted using a population-based registry and large numbers of input variables. Pearl et al., using numerous variables in creating a model of mortality prediction, definitely improved the performance of ANN [47]. On the other hand, their multiplicity hampers implementation of this model into a clinical practice. Most of previously designed ML approaches in outcome prediction after TBI, usually relay on large number of variables which might not be available at admission, i.e. length of stay [48]. The presented model, based on three simple variables (age, gender and ICD-10 code of sustained injury), was created in refer to resolve an issue underlined in previous studies. Comorbidities remain major prognostic factors in the prediction of outcomes after head injury [40]. In a database of almost 144,000 cases, used to design a predicting model in the current study, concomitant disease were found in only 3.6% of cases. It is believed that the low incidence of known cases with comorbidities will not significantly influence the outcome prediction in the current study.

Advantages of trauma scoring systems based on ICD-codes are widely known [49, 50]. It was therefore assumed that application of ICD-codes into a machine learning model could provide a high-quality, easy to use and precise tool for trauma mortality prediction. The only work published so far using the ICD-10 classification is that of Tran et al. [51], which also shows the high effectiveness of machine learning in predicting outcomes after trauma. Compared to the commonly used prognostic tools, such as ISS (AUC 0.828) and TMPM-ICD-10 (0.861), the ML learning model (XGBoost) using iterations of decision trees, achieved superior performance (AUC 0.863). Retrospective analysis of National Trauma Data Bank records was performed and a large group of 1.6 million patients was included in the analysis. The higher number of cases in the training set influenced the performance of the ML model. ICD-10 recognition code was the only available input variable. On the other hand, survival was the only output variable. In the current study, the ML algorithm based on a smaller group of patients with TBI was trained to predict potential death, survival or the need for further treatment. Three basic variables were used to train the network – age, gender and the ICD-10 recognition code, although the obtained effectiveness in predicting outcomes of about 81% is lower than in similar studies. Proposed model of mortality prediction is designed to develop previously described logistic regression models, based on ICD Classification. The ICISS score, found by Osler, was the first tool of mortality prediction among trauma victims where ICD codes were applied.

Recently published papers have focused on outcomes prediction among patients with brain injury, and proved the usefulness of ML models. Raj et al. presented a multicentre observational study of 472 patients treated because of TBI in Intensive Care Units in Finland [53]. The main purpose of the study was to develop a model for predicting dynamic changes in the prognosis of seriously injured patients. The researchers proposed a predictive model based on three variables with an accuracy of 81%. The presented algorithms were created using a frequently measured, by invasive techniques, parameters like Intracranial Pressure (ICP) or Cerebral Perfusion Pressure (CPP). Hsu et al. proposed a predictive model based on seven clinical and demographical measures [54]. Additionally, researchers tested different algorithms to determine the best predictor in mortality. Every tested model obtained a high accuracy of 91–93.2%.

To the best of the authors' knowledge, none of the recent studies focused on the usefulness of ICD-10 codes application into machine learning models in mortality prediction after brain injury. Considering the above-mentioned studies, higher accuracy of neural network was achieved in case of higher quality and differentiation of input variables. On the other hand, an increase in the number of variables from seven to fourteen did not improve the accuracy of the proposed models. In further research it is crucial to determine and measure the highest influence on patient survival, to create the most accurate model of mortality after TBI. The development of a machine learning model based on highly selected, easy to obtain variables, could result in the implementation of this prediction model into a clinical practice. The results obtained in the current study constitute the basis for further research on the use of artificial intelligence in this area.

Limitations of the study. The researchers faced several difficulties in designing the neural network, mainly due to the large number of cases, the number of which differed significantly between individual classification groups. Additionally, assigning a large number of deaths to one specific case of diagnosis (S06) is an important element. Another limitation of this study was data collection. The study was based on retrospective data collected from the NIPH / NIH. Records from The Nationwide General Hospital Morbidity (NHGM) is the only registry of trauma hospitalization in Poland, and its compilers emphasize that quality and incompleteness of data is the result of inappropriate completion of statistical forms by medical professionals [55]. Irrelevant and incomplete ICD codes of injury or comorbidities on discharge forms are a commonly known issue in Poland.

Nevertheless, the obtained research results are promising and indicate that neural networks can be a good alternative to the currently used trauma scales in the assessment of a patient after injury. In further studies, the authors plan to evaluate the use of neural networks in other types of injuries, and to compare their predictive value with the tools used so far.

CONCLUSIONS

Gender and age do not significantly influence the predictive value of ICD 10 based ANN in mortality prediction, but could be supporting variables. ICD 10 diagnosis has the greatest weight of mortality prediction. ICD 10 based ANN shows a moderate mortality prediction rate in patients with head and neck trauma; therefore, further studies with other input data and ANN algorithm are needed prior to the clinical use of this tool.

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