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APPLYING NEURAL NETWORKS TO HEALTH CARE QUALITY PARAMETERS

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For the purposes of monitoring and assessing the quality of care and treatment offered to patients and providing support for the activities related to health care, a quantitative indicator known as "indicator of quality in health care" is used. This study looked at the accuracy of forecasting case fatality rates using six distinct factors. Researching the relationship between the aforementioned factors (Death rate (percent) within 48 hours of admission, Surgery case fatality rate, The average length of hospital stay, The average number of pre-operative days, The average number of surgical procedures (anesthesia), The average number of nurses per occupied medical ward bed) and the prediction of the case fatality rate was the primary objective. Predictions of the case fatality rate will be made with the help of the Extreme Learning Machine (ELM) that will be built and utilized in the course of the research. Results from an ELM, a genetic programming (GP), and an artificial neural network (ANN) are contrasted and discussed. The accuracy of the computer models was assessed by comparing their predictions to empirical data and using a number of statistical measures. The results of simulations show that ELM may be used effectively in situations where the prediction of case fatality rates is required. *Acta Medica Medianae 2023;62(3): 17-23.*

***Key words**: case fatality rates, prediction, extreme learning machine*

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Introduction

We face new complexities in improving the structure and management of health care delivery, for example, increasing the integration of processes in care delivery for patient-centered chronic disease management (1, 2), as health care systems in developed nations transition to a value-based, patient-centered model of care delivery (3). New technologies, including artificial intelligence, have the ability to handle non-traditional care settings, the changing healthcare workplace and workforce, and the introduction of new fragmented health information systems, all while providing cost-effective and appropriate treatment in real-time (3). There is a dearth of guidance on selecting appropriate methods that are tailored to the health care industry (2), despite the fact that there is a plethora of solutions capable of addressing these health care management challenges due to the widespread use of artificial intelligence for making complex decisions across a wide range of industries.

Aging populations, illness complexity, medical treatment advancements, rising labor costs, and the growth of the health care industry are expected to cause global health care spending to approach $8.7 trillion by 2020. It has been reported that many hospitals and other medical facilities cannot afford to upgrade their aging facilities and legacy equipment. Reportedly, decision-makers are shifting their focus to understanding and better aligning financial incentives for health care providers in order to assess the financial risk; population health management, including analyses of health, quality, and cost trends; and adoption of innovative delivery models for improved processes and coordination of care in order to make the transition to value-based care (1, 2).

Health care organizations need to be more strategically managed due to system interdependencies such as shifting environmental demands and competing objectives that may complicate the decision-making process (4). Most companies are risk-averse (5), and healthcare decision-makers may face cultural, technological, and risk-related obstacles when making high-risk decisions without a guarantee of a high return (5, 6). Both clinical (such as diagnosis, treatment and therapy, medicine prescription and administration) and non-clinical (such as budget, resource allocation, technology acquisition, service additions/reductions, strategic planning) decisions need input from several parties (1, 7).

According to a white paper published by IBM, (8) health care providers are increasingly analyzing massive sets of routinely collected digital information in an effort to improve service and cut costs as the collection and digitalization of health care data (such as electronic medical records and DNA sequences) continues to rise. Concerns regarding the effectiveness of programs may be addressed, for instance, by analyzing clinical, financial, and operational data and making predictions about patients who are at risk. By 2025, the global market for health care predictive analytics is expected to rise from its 2015 value of $1.48 billion at a CAGR of 29.3 percent (9). Equally promising is the forecasted growth of the artificial intelligence (AI) market for healthcare applications, which is expected to increase by 40% (Compound Annual Growth Rate) by 2021, leading to global revenue of $811 million. The health care business is expected to be a major driver of the MLaaS market, which is projected to grow to $5.4 billion by 2022 (10).

In a recent survey of AI's medical applications, artificial neural networks (ANN) were found to be among the most often used machine learning techniques (11). Several significant diseases, including cancer and cardiovascular disease, benefited from this approach. Applications of ANN in healthcare include clinical diagnosis, cancer prediction, speech recognition, hospital stay length prediction (12), image analysis and interpretation (13) (for example, automated electrocardiographic (ECG) interpretation used to diagnose myocardial infarction (14)), and drug development (13). Health care analytics have applications outside of patient care, including improved organizational management (15) and improved forecasting of key factors like cost or facility use (16). The use of ANN in decision support models has resulted in more efficient use of both medical professionals' and the healthcare system's time and resources (17).

Methodology

Though ANN has seen increasing use in recent years (18), there is still room for improvement in how well it can inform choices at different tiers of healthcare organizations. The motivation for this research was the lack of a thorough understanding of ANN's various applications in healthcare, and it is hoped that this work would be of assistance to scholars working to bridge the gap between organizational psychology and computer science. It may be challenging to keep up with the newest advances and trends in ANN applications (19), given the enormous number of reported uses and the complexity of the subject. Newcomers to the field of artificial intelligence (AI) or ANN adopters may find the vastness and esoteric terminology of neural computing to be particularly challenging (19). Current literature evaluations of ANN applications are either too narrow in scope (i.e., they concentrate on data mining or AI approaches that may contain ANN but do not give insights particular to ANN) or too wide (i.e., they focus on a specific illness (20) or a certain kind of neural network (21)). The major goal of this scoping research is to provide a comprehensive examination of the many ANN applications in health care organization and decision-making at the micro, meso, and macro levels. Decisions about resource allocation or utilization can be made at three distinct levels: the individual patient's (micro) level, the group's (meso) level (e.g., the department's or organization's) level, where patient preference may be important but is not essential, and the public sector's (macro) level (22). We will examine the approach and context used, as well as identify the nature and extent of the applicable literature, by conducting this review. As Kononenko (2001) summarizes, the discipline of artificial intelligence (AI) that deals with machine learning provides essential resources for the intelligent processing of data. As electronic computers were widely available in the 1950s and 1960s, three major subfields of machine learning—statistical methods, symbolic learning, and neural networks—emerged (23). The physical sciences have found success in using ANN to tackle difficult problems, and more recently, scholars in organizational research have found success in using ANN as digital tools to speed up data collection and processing (24). ANN are flexible and useful modeling techniques because of their ability to extend pattern knowledge to new data, tolerating noisy inputs, and producing accurate and acceptable estimations (24). ANN belong to the larger family of flexible nonlinear regression and discriminant models, data reduction models, and nonlinear dynamical systems (25). In terms of their statistical similarities, ANN may be compared to generalized linear models, nonparametric regression, discriminant analysis, and cluster analysis (25). Its general structure as a statistical model is made up of basic, connected processing units that are trained on new sample data over and over again (24). Its use is most helpful in situations where the theoretical basis for prediction is unclear, such as when sample data exhibit complex interaction effects or do not meet parametric assumptions, when the relationship between independent and dependent variables is weak, when there is a large amount of unexplained variance in information, or when there is a lack of information. Single-layer perceptrons, multi-layer perceptrons, and radial basis function networks are examples of feed-forward neural networks, whereas examples of feed-back or recurrent neural networks include Competitive networks, Kohonen's self-organizing maps, and Hopfield networks (26). Data used in this research is obtained by desk research of different national health systems in World Health Statistics 2022 (27), European Health for All database (28) and The World Bank Health, Nutrition and Population (29). ANN methodology applied is based on MATLAB ANFIS software modified to meet requirements of research scope (30). The research is a part of the project of applying ANN to the management of human resources in healthcare and in the prediction of public health parameters with the aim of defining how to apply ANN to causal interpersonal and multifactorial relationships, carried out at the Department of Management of the Faculty of Mechanical Engineering in Niš. All relevant input and output parameters for this study are included in Table 1.

Table 1. Input and output parameters

Inputs	Parameters description
Input 1	Death rate (%) within 48 hours of admission
Input 2	Surgery case fatality rate
Input 3	The average length of hospital stay
Input 4	Average number of pre-operative days
Input 5	Average number of surgical procedures (anesthesia)
Input 6	Average number of nurses per occupied medical ward bed
Output	Case fatality rate

ANN

To process information, ANNs use processing units (nodes or neurons) that are coupled by a set of tunable weights so that signals may move both concurrently and sequentially across the network (14, 31). ANNs can contain anywhere from a single to numerous layers. In general, ANNs can be thought of as consisting of three tiers, or layers, of neurons: the input layer, which processes incoming data, the hidden layer, which is responsible for pattern extraction and does the bulk of the network's internal processing, and the output layer, which displays the results of the network's work.

According to a review written by Agatonovic-Kustrin and Beresford (2000), neurons in a neural network draw their energy from one another, and each neuron has a single output, a transfer function, and a weighted input. According to the authors, a single output is generated by the neuron after a transfer function has processed an activation signal based on a weighted sum of all inputs to the neuron. General network behavior is determined by transfer functions, learning rule, and network architecture (31). Nonlinear statistical modeling using ANN offers additional options to the standard approach of creating predictive models for dichotomous outcomes in medicine, logistic regression (32). The networks can identify complicated non-linear correlations and interactions between dependent and independent variables, and users may do so with less formal statistical expertise. ANN may use both theoretical and empirical evidence to find answers to difficulties (31). Other benefits of ANN over conventional predictive modeling methods include its ability to learn inductively from training data and process non-linear functionality critical to dealing with real-world data, as well as its speed and simplicity of operation due to compact representation of knowledge (e.g., weight and threshold value matrices). Despite the fact that ANN do not need data-source knowledge, they still need big training sets because of all the projected weights (31). They may take a while to train, and getting varied results by using alternative weight initializations (32-36) is possible. While ANN have been put to good use, they still present challenges since we have very little understanding of how they learn or the scope of the information they contain (35). The literature identifies a number of problems with ANN, including their inability to explicitly identify potential causal relationships, their difficulty of use in the field, their susceptibility to over fitting, the fact that model development is empirical, which could mean it takes multiple attempts to develop an acceptable model, and the presence of methodological issues related to model development (37-42). Tu (1996) outlines the pros and cons of utilizing ANN to predict medical outcomes, arguing that logistic regression models can be shared with more people whereas ANN models are less easy to understand and hence more challenging to implement. However, logistic regression coefficients may be made public for use by any user, while ANN connection weight matrices used for training a data set may be too vast and complicated for others to utilize, even if made publicly accessible (1, 36).

Results and discussion

Here we provide the ELM prediction model's performance results for predicting case fatality rates using the values from Table 1. The ELM model achieves an adequate level of prediction accuracy. Observe that the majority of the data points lie on the diagonal. Thus, the ELM method's predicted values accord with the observed values to a high degree. An adequate coefficient of determination permits confirmation of this finding. Inaccurate estimates or projections are rare. Accordingly, it can be shown that the projected values have a very high degree of accuracy.

Performance comparison of ELM, ANN and GP

The prediction accuracy of the ELM models was compared to the prediction accuracy of the ANN and GP, which were used as benchmarks, to show the benefits of the proposed ELM technique more clearly and convincingly. The traditional statistical error indices (RMSE and R2) were employed for comparison. The findings from the forecasts are summarized in Table 2.

Table 2: Comparative performance statistics of the ELM, ANN and GP models for case fatality rate prediction in training ELM

		ANN		GP	
RMSE	R^2	RMSE	R^2	RMSE	R^2
0.1910	0.9926	0.2453	0.9878	0.3561	0.9743

Conclusion

One of the driving forces for the introduction of quality indicators in health care is the need to reduce cost, a priority in all sectors of the economy. This was accomplished via better process management. As a result, the efficiency of the healthcare system overall improves, as the chance for errors during treatment is greatly reduced, and the cost associated with duplicative efforts are cut down. It's important to note that process management in terms of health care quality indicators is a cornerstone of the idea of contemporary medicine. To put it simply, this basis is crucial to the practice of contemporary medicine. The high number of signs and factors that affect the case fatality rate makes precise forecasting of the case fatality rate in the future challenging. Therefore, this study offered a fresh approach to addressing the challenges of predicting the case fatality rate. In this approach, we discard non-critical features of the input data.

Due to the many signs and factors that affect the case fatality rate, it is challenging to make an accurate prognosis of the case fatality rate in the future. Since this is the case, the findings reported here provide a unique approach to HHI forecasting that makes use of soft computing methods in order to circumvent the aforementioned challenges.

An efficient learning model based on ELM was developed to predict the case fatality rate with high accuracy. In comparison to the results of the ANN and GP, the accuracy of the forecasted values was assessed. It was shown via simulation that the ELM model had the best potential for estimating the case fatality rate. The ELM technique has potential use in estimating fatality rates and other applications where the fatality rate is relevant. This is true in the broad and the +narrow sense.

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PRIMENA NEURONSKIH MREŽA NA PARAMETRE KVALITETA ZDRAVSTVENE ZAŠTITE

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Za potrebe praćenja i procene kvaliteta nege i lečenja koji se nude pacijentima i pružanja podrške aktivnostima koje se odnose na zdravstvenu zaštitu koristi se kvantitativni indikator poznat kao „indikator kvaliteta u zdravstvenoj zaštiti". Ova studija je razmatrala tačnost predviđanja stope smrtnosti slučajeva koristeći šest različitih faktora. Istraživanje odnosa između navedenih faktora (stopa smrtnosti (procenat) u roku od 48 sati od prijema, stopa smrtnosti hirurških slučajeva, prosečna dužina boravka u bolnici, prosečan broj preoperativnih dana, prosečan broj hirurških zahvata (anestezija), prosečan broj medicinskih sestara po zauzetom krevetu na medicinskom odeljenju) i predviđanje stope smrtnosti slučaja bili su primarni cilj. Predviđanja stope smrtnosti slučajeva urađena su uz pomoć mašine za ekstremno učenje (ELM), izgrađene i korišćene u toku istraživanja. Rezultati ELM-a, genetskog programiranja (GP) i veštačke neuronske mreže (ANN) bili su predmet poređenja i diskusije. Tačnost kompjuterskih modela procenjena je upoređivanjem njihovih predviđanja sa empirijskim podacima i korišćenjem niza statističkih mera. Rezultati simulacija pokazuju da se ELM može efikasno koristiti u situacijama kada je potrebno predviđanje stope smrtnosti. *Acta Medica Medianae 2023; 62(3):17-23.*

***Ključne reči**: stopa smrtnosti, predviđanje, mašina za ekstremno učenje*