

The implementation of neural network in the risk stratification for mortality in myocardial infarction survivors

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Abstract

The review article is dedicated to the issue of the implementation of neural network in the risk stratification for mortality after myocardial infarction. The advantages of neural network over widely used prognostic scales are discussed. The examples of the development of such models are presented.

Keywords: myocardial infarction, risk stratification, machine learning, neural network.

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Introduction

Machine learning is computational process that uses input data to achieve the certain goal, not by directly programming the desired result [1]. Such algorithms are used to build systems that automatically improve through experience. The process of adaptation, when input data and desired result are inserted into the program, is called learning. Then algorithm is modified not only due to produce with the learning data, but also based on new data [2].

Artificial neural networks in cardiology, textual data analysis

The quality of machine learning model primally depends on the sample size that is used for learning [1]. In medical science the largest samples with patient's characteristics are data registers [1].

For the quality control of machine learning most scientists prefer to use the results of the logistic regression or TIMI and GRACE scales [3,4]. The main advantage of machine learning is wider range of data that is used for prognosing. Widely used scales are outdated and cannot provide modern patients with high quality prognosis due to changes in approaches to antiplatelet therapy prescription, the use of drug-eluting stents, and the possibility of modifying samples that are used for learning over time. Another advantage of machine learning is that such models can consider regional features and, as the result, provide better forecast compared with scales developed in other regions [5].

Artificial neural networks for the prognosis of outcomes in patients with myocardial infarction

Sherazi et al. developed prediction model based on data from Korea Acute Myocardial Infarction (MI) Registry (KAMIR) in 2020 [6]. Patients who failed to follow up after hospital and patients who died during hospital admission were excluded from the study [7]. Thus, sample size was 8227 patients including 395 deaths after hospital discharge.

Study subjects were then subdivided into training and testing data sets with the ratio of 80% to 20%, respectively. One of the most significant limitations of

the study was no division of the outcomes into cardiac and non-cardiac mortality. The following variables were used for the mortality prediction model: demographical, clinical, biochemical parameters, Killip classification class and lesion type [8], echocardiographic parameters, the presence of concomitant diseases, medication characteristics of patients; angiographic, echocardiographic parameters, results of percutaneous coronary intervention (PCI), PCI stent types. Four different machine learning models were developed based on the following algorithms: gradient boosting machine (GBM), generalized linear model (GLM), deep neural network (DNN), random forest (RF) [9]. After the training process, the results of machine learning-based mortality prediction models were compared with GRACE scale [4]. The GBM and DNN models had the AUC of 0.898 and 0.898, respectively, that was superior to GRACE. D'Ascenzo et al. performed the study where aimed to predict three outcomes: all-cause death, recurrent acute myocardial infarction, and major bleeding after acute myocardial infarction [10]. Study participants were obtained from two registries: the BleeMACS registry (n=15 401) [11] that included patients from North and South America, Europe, and Asia, and the RENAMI registry (n=4425) that included patients from Europe [12]. The data from two registers were combined and then randomized. The next step was the random split of cohort into two datasets: training (80%) cohort, and testing (20%) (internal validation) cohort. The main feature of this study was the use of internal validation group as the control group. The external validation cohort included 3444 patients from the European SECURITY randomized controlled trial [13], 1465 patients from two prospective registries from the University of Ferrara [14], and 1537 patients from the Clinical Governance in Patients with ACS project of the Fondazione IRCSS [15]. Such approach allows to exclude overfitting error when running the model. Overfitting happens when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data [16]. Patients were described with clinical data and medication characteristics and angiographic data. Several machine learning algorithms were

tested during model development, and the adaptive boosting algorithm was the most successful learning model. The final model was called PRAISE risk score and can be used as online calculator [17]. The prediction results for one year mortality show high quality prognostic value for developed model [18]. Data are presented in table 1.

Conclusion

Neural network can effectively predict mortality during one year follow-up in patients after myocardial infarction and can be used as promising direction in prevention of adverse cardiovascular events. Machine learning needs to be developed and implemented into practice both in world and domestic medicine, since high-quality prediction of mortality risks allows practitioners to identify high-risk patients and, as the result, prevent their deaths.

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Table 1. The quality of PRAISE risk score predictoin

Outcome predictions	AUC	CI
Prediction quality in training cohort		
All-cause mortality	0.91	0.90–0.92
Recurrent acute myocardial infarction	0.88	0.86–0.89
Bleeding	0.87	0.85–0.88
Prediction quality in internal validation cohort		
All-cause mortality	0.82	0.78–0.85
Recurrent acute myocardial infarction	0.74	0.70–0.78
Bleeding	0.70	0.66–0.75
Prediction quality in external validation cohort		
All-cause mortality	0.92	0.90–0.93
Recurrent acute myocardial infarction	0.81	0.66–0.85
Bleeding	0.86	0.82–0.89

Comment. AUC — area under curve (площадь под кривой);
CI — confidence interval.

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