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Evaluation of the effectiveness of using artificial intelligence to predict the response of the human body to cardiovascular diseases

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Abstract. This article discusses the issue of assessing the quality of predicting the dynamics of the human body in conditions of cardiovascular disease using intelligent software systems. To improve the forecast accuracy, the voting method of 3 competing systems was used, as well as the elimination of sparse data columns. Assessment of the quality of the prognosis of complications of cardiovascular diseases is carried out in terms of the accuracy and specificity of the diagnosis. The constructed system for 10 predicted diagnoses out of 12 showed a prediction accuracy of more than 90% with a specificity of more than 85%. This result shows a fairly high predictive ability of the created system when solving the problem of predicting the reaction of the human body to the onset of cardiovascular diseases (for example, complications of myocardial infarction).

1. Introduction

The severity of the problem of cardiovascular diseases is confirmed by numerous statistical data [1]. In developed countries, heart disease and stroke are the first and the second leading causes of death among adult men and women. In developing countries, CVD deaths are twice as common as in developed countries [2]. Overall, developing countries have CVDs occupy the third highest diseases' proportion in developing countries. Cardiovascular diseases accounted for more than a third of recorded deaths in the UK (38%).

Such a high problem's severity keeps us look for new approaches to prevention, treatment and rehabilitation of patients with this disease. To solve these problems, it is necessary to improve methods for predicting the course and outcomes of acute myocardial infarction. Many authors have predicted the course of myocardial infarction based on clinical, laboratory and clinical instrumental data. Often, clinical data processed using various mathematical methods are used for prognosis. In particular, forecasting methods with the calculation of predictive indices were proposed (A. Peel [2]), discriminant analysis was applied, and attempts were made to use image recognition algorithms. At the same time, artificial neural networks (ANN) have a significant advantage over classical linear or statistical methods (for example, implemented in MS Excel, Statistica) due to effectively implemented self-learning algorithms [3].



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However, this approach also has a significant disadvantage – the requirement for a large sample of clinical cases with a known outcome. The artificial neural network's formation architecture includes actions both to change the artificial neural network's topology and to select the number of trained parameters. In the development's process of artificial neural network technology, the “deep learning” approach has emerged. The artificial neural networks allow detecting relationships between the studied features, which are not always obvious by studying statistical analysis' traditional methods.

Attempts to use neural networks to predict the course and consequences of cardiovascular diseases have been made since the early 90's (D. Rossiev et al. [4], Gorban et al. [5]). Work in this direction continues at the present (Eggers et al. [6]). Currently, the work is extended to the field of interpretation of cardiograms (see, for example, Mena et al. [7]).

Artificial neural networks are widely used in the development of expert systems designed to predict the course of cardiovascular diseases. Meyer et al. proposed [8] to use a recurrent ANN to predict serious complications during intensive care in real-time after open heart surgery.

The course of the disease in patients with MI is different. MI can be uneventful or have complications that do not worsen the long-term prognosis. At the same time, about half of patients in the acute and subacute periods have complications leading to a worsening of the course of the disease and even death. Even an experienced professional cannot always predict the development of these complications. In this regard, predicting the complications of myocardial infarction to timely carry out the necessary preventive measures is an important task. At the same time, high requirements for the sample size for training ANN require the use of special methods to increase the predictive ability of the developed neural network expert systems for cardiological purposes. This article is devoted to solving this problem.

2. Methods

The object of the research is a database of case histories of patients with myocardial infarction [9]. The database is provided with a corresponding description and was assembled in 1989-1995 in Krasnoyarsk. Of the 1,700 patients with MI, there were 1,065 (62.6%) men and 635 (37.4%) women. The localization of myocardial infarction was as follows: infarction mainly of the anterior wall, including the anterior, anterior septal, anterior apical, and middle lateral ones - in 885 (52.1%) patients; posterior diaphragmatic (lower) - in 542 (31.9%) patients; posterior basal (posterior) MI in 47 (2.8%), inferior and lateral wall MI - in 52 (3.1%) patients, inferior and posterior wall MI - in 101 (5.9%) patients, circular MI - in 73 (4.2%). MI of the right ventricle occurred in 50 (2.9%) patients. Transmural (large-focal) MI (QRS complex of the QS or QR type) occurred in 1141 (67.1%) patients, non-transmural MI - in 559 (32.9%) patients.

The following diseases preceded the present MI: angina pectoris in 933 (54.9%) patients, MI in 636 (37.4%), hypertension in 1086 (63.9%), symptomatic hypertension in 56 (3.3%), chronic heart failure in 178 (10.5%), diabetes mellitus in 228 (13.4%), obesity in 43 (2.5%), thyrotoxicosis in 13 (0.8%), cardiac arrhythmias in 134 (7, 9%), conduction disorders in 28 (1.6%). chronic lung diseases in 323 (19.0%).

During the period of hospital stay, atrial fibrillation (AF) was observed in 170 (10.0%) patients, ventricular fibrillation (VF) in 71 (4.2%), pulmonary edema (OB) in 159 (9.4%), heart rupture (MS) in 54 (3.2%), death (LI) in 271 (15.9%).

Patient demographics are shown in figure 1. It can be seen that up to the age of about 65 years, men predominate among patients, and at older ages, women. This distribution quite accurately corresponds to the ratio of the duration of women and men in the Russian Federation for the period of the database [9] collection.

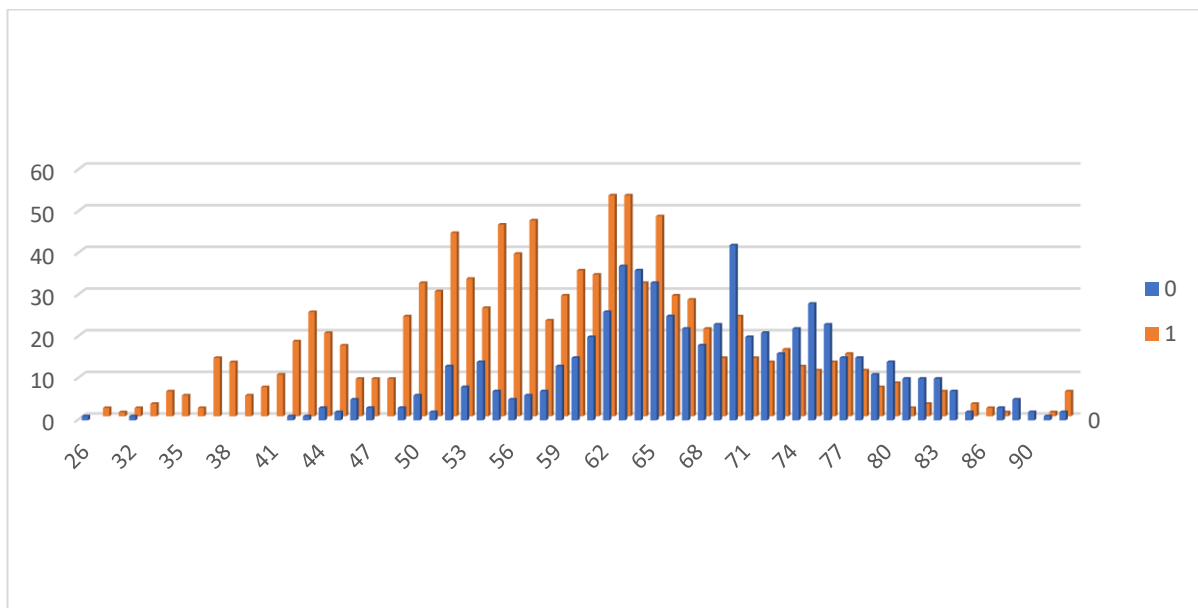


Figure 1. Distribution of patients by age and sex composition (0 - women, 1 - men).

Figure 2 shows the distribution of patient mortality (data for the LET_ISH field) by sex (SEX field) and age (AGE field). It can be seen that the sample, like figure 1, corresponds to the demographic statistics in Russia for the period of database [9], the peak of mortality in men from complications of myocardial infarction falls at a significantly earlier age than for women.

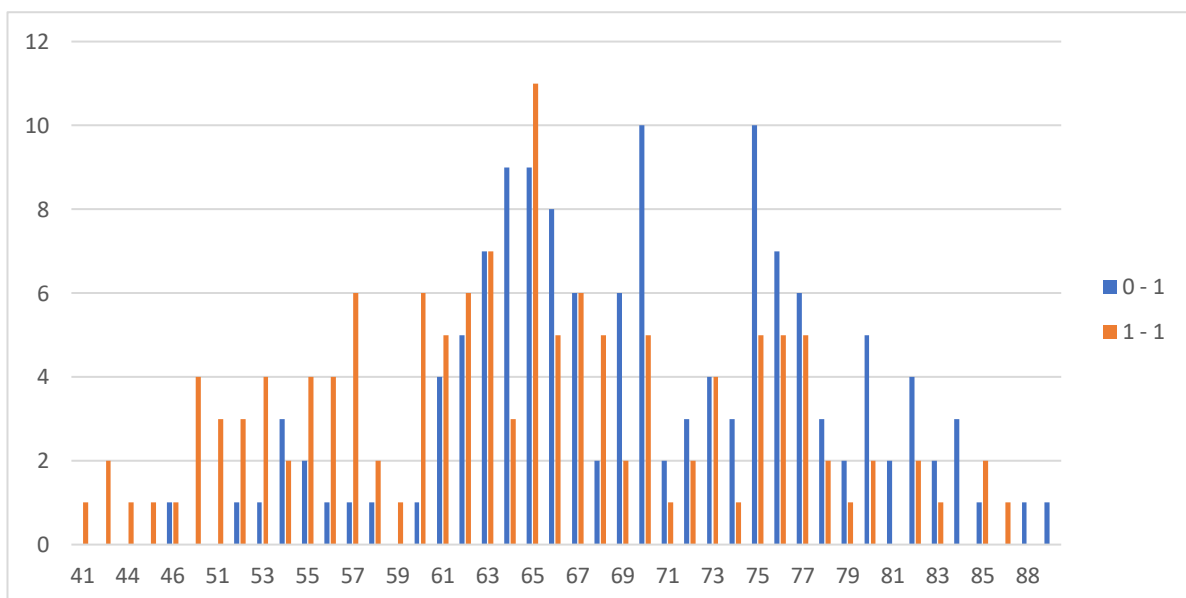


Figure 2. Patient mortality by age (0-1 - women, 1-1 - men).

The prediction was performed by using the Matlab 2016 system, the NeuralNetworkToolbox module [10]. During the study, we selected the neural network architecture that best predicts the outcomes described in the database.

The task was to predict the following disease outcomes encoded in the database fields [9]:

- A_V_BLOK - (Third-Degree Atrioventricular Block ECG);

- DRESSLER - Dressler syndrome;
- FIBR_JELUD - Ventricular fibrillation;
- FIBR_PREDS - Atrial fibrillation;
- JELUD_TAH - Ventricular tachycardia;
- LET_IS - Lethal outcome;
- OTEK_LANC - Pulmonary edema (Pulmonary edema);
- P_IM_STEN - Postinfarction angina (Post-infarction angina);
- PREDS_TAH - Supraventricular tachycardia;
- RAZRIV - Myocardial rupture;
- REC_IM - Relapse of the myocardial infarction;
- ZSN - Chronic heart failure.

The distribution of diagnoses in the database [9] by the gender composition of patients is shown in table 1.

Table 1. Distribution of diagnoses by sex composition of patients.

Diagnoses	Women	Men
FIBR_PREDS	89	81
PREDS_TAH	9	11
JELUD_TAH	10	32
FIBR_JELUD	22	49
A_V_BLOK	20	37
OTEK_LANC	75	84
RAZRIV	31	23
DRESSLER	22	53
ZSN	181	213
REC_IM	75	84
P_IM_STEN	59	89
LET_IS	137	134

In all experiments, artificial neural networks of direct propagation (*feedforwardnet* function) were used for forecasting. The neural network created this function using contains a set of several layers. The first (input) layer connects the network to the input data vector. Then there are two hidden layers of neurons (60 neurons and 40 neurons, respectively), and each subsequent layer is connected to the previous one. The last (output) layer calculates the output signal of the network, which is responsible for predicting the occurrence of one of the diagnoses. The diagnosis by the neural network was determined as follows. The presence of the relevant diagnosis in the medical history was coded in the database with the value "1" and the absence of a diagnosis of a "0". And if the output signal of a neuron exceeds the value "0.5", the diagnosis was considered delivered, if not exceeded, then it was assumed that the appropriate diagnosis is missing.

The neural network was trained with a teacher using the *traingdx* training function, which performs training using the back propagation of error method with optimization of the error function using the gradient descent method. In addition, for prediction the diagnosis of multiple networks generated with different starting markings of synapse weights the traditional method for medical applications of neural networks was used. This approach is called "Concilium". Weighing the opinions of multiple networks can be performed by averaging the corresponding output signals. In this work, the voting method was used - the diagnosis was made, which was made by a simple majority of the voting neural networks.

ANN architecture and parameters of the learning process, see figure 3

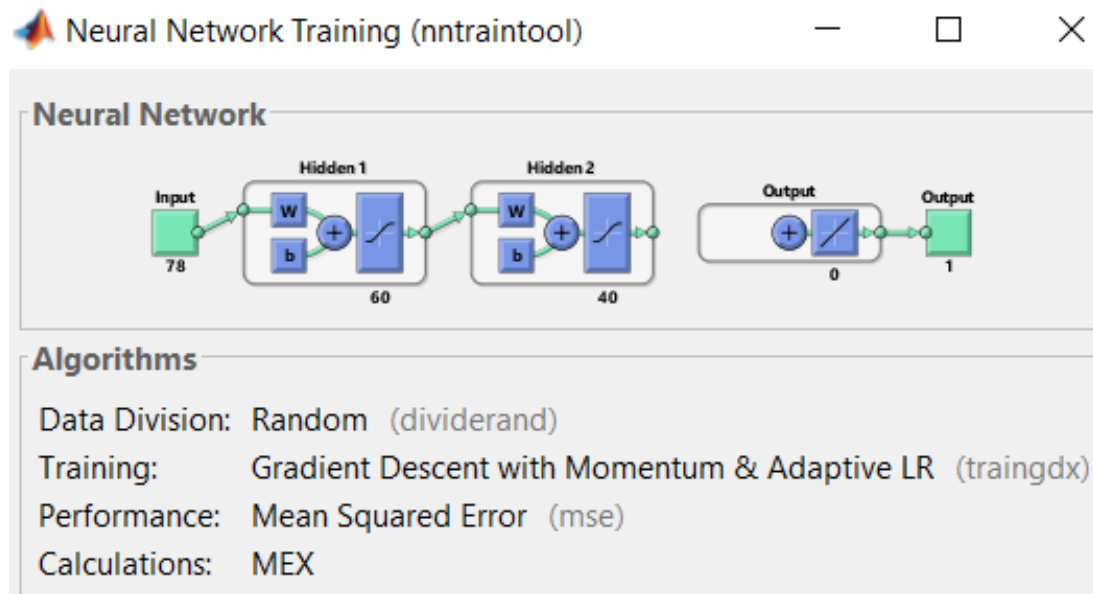


Figure 3. An example of the Matlab neural network architecture used in the forecast.

The decision on the diagnosis was made by a council of neural networks using the voting method. Let Λ be a set of features (in this paper, diagnoses), and $\Lambda_j, j = 1..J$, be reference sets, $\Lambda \subset U, \Lambda_j \subset U, \Lambda(J) = \bigcup \Lambda_j$ be the union of sets of reference signs (in this work - a complete set of diagnoses in the database [9]). We represent the recognition problem as establishing the equivalence of Λ to one of the sets Λ_j . $r(\Lambda)$ - a measure of proximity of the sets Λ and Λ_j , subject to the property of analysis of incomplete descriptions, can be calculated by "voting" elements. This corresponds to the rule of identifying a set "by composition". The value of the measure is incremented if the element $\lambda \in \Lambda$ has in some sense an element equivalent to it from $\Lambda(J)$. In the set-theoretic representation, voting is reduced to constructing on the set Λ a representation $\Lambda(J) = \bigcup \Lambda_j$ in the form of a partition (disjoint subsets, $\Lambda_i \cap_{i \neq j} \Lambda_j = \emptyset$ or a covering $\Lambda_i \cap_{i \neq j} \Lambda_j \neq \emptyset$) consisting of elements labeled with class $j = 1..J$ by realizing the mapping $\Lambda \rightarrow \Lambda_j$. The decision on the class of the object with the description Λ is made by the deciding coalition corresponding to the feature, the number of votes of which corresponds to the highest power among $\{\Lambda_j\}$. The minimum size of the coalition depends on the level of distortion; in our problem, the size of the coalition corresponds to the size of the Concilium (number of voting ANN's).

To increase the efficiency of using the database data, the learning process was carried out by the "sliding window" method. This method consists of excluding only one example of the source database from the training sample and testing the trained neural network on the excluded example. Thus, for a single session, you need to train a number of neural networks equal to the number of examples of the training sample.

The optimal use of the informativeness of the training sample was ensured by the use of the control method for individual objects (leave-one-out CV) when teaching the ANN.

In the general case, the sliding control estimate is constructed over all $N = C_L^k$, where L is the total number of examples, k is the number of examples excluded from training and used for testing. A special case of splitting when $k = 1$ is called a "leave-one-out CV". It was shown in [11] that, under certain conditions, control over individual objects is asymptotically optimal. Probability value:

$$\frac{L_n(\hat{m})}{\inf_{m \in M_n} L_n(m)} \rightarrow 1, \text{ where}$$

M_n – class of compared models

$L_n(\hat{m})$ – mean square error when choosing model m

$$\hat{m} = \arg \min_{m \in M_n} CV(n)$$

The quality of the neural network's prediction of the consequences of myocardial infarction was evaluated by standard indicators designed to assess the effectiveness of diagnostic methods – Accuracy and Specificity.

Accuracy is an indicator that allows you to compare different methods for determining the same indicator when examining a single population of patients. It represents the number of true results to the number of all survey results.

A sensitive test should be selected if there is a risk of missing the disease with an unclear diagnostic picture or to narrow the scope of the diagnostic search by eliminating a number of common causes using highly sensitive tests. Sensitivity is the number of correct positive results of the examination to the patients examined total number.

Specificity indicates the number of correct negative survey results to the total number of the control group. Specific tests are needed to confirm a diagnosis based on other data. Highly specific tests are especially necessary if a false positive result can cause harm to the patient, for example, as a result of incorrectly prescribed treatment.

3. Results

For this neural network's configuration, the forecast of all twelve diagnoses contained in the database was calculated. Also, the following indicators varied:

- Using a network consultation – the forecast options were checked by a single neural network, as well as by a consultation of 3 networks that make decisions by voting.
- Eliminate the sparsest input data columns, including no more than 40 cases out of a total sample of 1700 cases.

The calculation results for the accuracy, sensitivity and specificity of predicting the consequences of myocardial infarction by the councils of artificial neural networks are given in Tables 2 and 3, respectively.

Table 2. The accuracy of predicting the myocardial infarction consequences of artificial neural networks.

	Contrast	All		40+	
		1	3	1	3
	K=				
Diagnosis	FIBR_PREDS	87.93%	89.94%	87.46%	89.17%
	PREDS_TAH	97.76%	98.76%	97.41%	98.71%
	JELUD_TAH	96.29%	97.47%	96.41%	97.41%
	FIBR_JELUD	94.53%	95.64%	94.23%	95.70%
	A_V_BLOK	95.82%	96.59%	94.76%	96.47%
	OTEK_LANC	89.64%	90.11%	89.05%	90.46%
	RAZRIV	95.47%	96.70%	95.29%	96.70%
	DRESSLER	94.06%	95.53%	93.88%	95.47%
	ZSN	75.16%	75.57%	73.16%	75.46%
	REC_IM	88.82%	90.64%	88.29%	90.46%
	P_IM_STEN	89.35%	91.23%	89.58%	90.99%
	LET_IS	77.40%	81.81%	73.69%	79.87%

Table 3. The specificity of predicting the myocardial infarction consequences of artificial neural networks.

	Contrast	All		40+	
	K=	1	3	1	3
Diagnosis	FIBR_PREDS	90.17%	90.18%	90.27%	90.01%
	PREDS_TAH	98.81%	98.82%	98.81%	98.82%
	JELUD_TAH	97.50%	97.53%	97.56%	97.53%
	FIBR_JELUD	95.82%	95.81%	95.86%	95.82%
	A_V_BLOK	96.67%	96.64%	96.64%	96.64%
	OTEK_LANC	90.89%	90.59%	91.13%	90.77%
	RAZRIV	96.78%	96.82%	96.77%	96.82%
	DRESSLER	95.57%	95.58%	95.51%	95.58%
	ZSN	78.36%	77.37%	78.21%	77.54%
	REC_IM	90.66%	90.79%	90.61%	90.63%
	P_IM_STEN	91.22%	91.28%	91.44%	91.26%
	LET_IS	85.40%	85.14%	85.24%	85.38%

4. Discussion

The obtained prediction results suggest that the artificial neural network has a fairly high predictive ability to predict the outcomes of myocardial infarction. In table 2, you can see that 9 out of 12 diagnoses are predicted by the neural network of the selected architecture with an accuracy of more than 90%, and only one is predicted with an accuracy of less than 80%. At the same time, the indicator of the specificity of the diagnosis (Table 2) remains practically unchanged. Thus, even a fairly modest database size (1700 records) allows you to train neural networks that allow you to accurately predict the outcomes of the disease.

As opposed to previous studies, the hypothesis about the effectiveness of excluding sparse data columns to improve the accuracy of predicting the outcome of the disease was not confirmed. Table 2 shows that excluding sparse columns (containing no more than 40 non-zero values) had virtually no effect on the accuracy of the forecast.

The effectiveness of the neural network consultation was confirmed. Table 2 shows that the transition to a diagnosis by a council of 3 neural networks instead of one neural network of the same architecture can increase the forecast accuracy by 1-2%.

In General, you can see that all the approaches used to improve the accuracy of forecasts gave an increase in the probability of correct diagnosis in a total of 2%. The best configurations of neural network consultations provided about 95% accuracy for 3 out of 12 diagnoses with up to 98% specificity. Accuracy of more than 90% was achieved for 10 out of 12 diagnoses, the worst result is 80% accuracy with 85% specificity.

5. Conclusion

The study of the prediction quality consequences of the myocardial infarction by using neural networks shows fairly high accuracy and specificity of this method. It is shown that the consensus of neural networks operating by the voting method using increases the accuracy of the forecast for all diagnoses.

Prospects for further work are as follows:

- Use a more up-to-date database in training than we used in the study [9]. Such a database should include a larger number of input parameters, as well as a larger number of cases. A more balanced database should be sought, including more evenly diagnosed and undiagnosed cases.

- In addition to the listed forecast quality indicators, you should verify a sensitivity indicator that evaluates the ratio of correct and incorrect positive tests.
- In the transition to the neural network expert system development for predicting the consequences of myocardial infarction on specialized platforms for the development of neural network models, for example, TensorFlow / Keras.

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