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PREDICTION OF SURGERY CONTROL PARAMETERS IN CARDIOLOGY TO OPTIMIZE THE EMISSION FRACTION VALUES WITH THE HELP OF NEURAL NETWORKS

Introduction. *In the Big Data era, decision tree methods, machine learning, and neural networks, along with other Data Mining methods became an alternative to classical statistical methods as a more useful tool for analyzing large and inhomogeneous data. Neural Networks methods have emerged as a more accurate and effective technology in a wide range of medical problems such as diagnosis, prediction, treatment.*

The purpose *of the paper is to indentificate the control parameters of the surgical intervention to optimize the EF ejection fraction after the surgery using a Data Mining method (neural network) models.*

Results. *The analysis of changes in hemodynamic parameters of children with severe heart defects due to surgery — implantation of conduit. Changes in these parameters after surgery were analyzed using analysis of variance for repeated measurements (RepANOVA).*

It was determined that after the surgery *there was a significant, statistically significant decrease in 3 hemodynamic parameters (end diastolic index, aortic pressure gradient, and augmentation index). According to the cluster analysis, three groups of patients were identified, which were differed in all hemodynamic parameters and in the peculiarities of changes in the studied parameters after surgery. A model based on a neural network of the RBF type (with radial-based activation functions) was built using the Data Mining Automated Neural Networks module of the STATISTICA package. According to the developed models, the dependence of the emission fraction after the* surgery *on the control parameters — dopamine dose and conduit diameter was determined.*

Conclusions. *The use of predictive models of neural networks developed by the type of RBF network with radially symmetric functions in single-layer networks, allowed to analyze the effectiveness of surgical interventions in the case of congenital heart disease in infants and children. Taking into account the results of the developed prognostic model of the dependence of the cardiac output fraction on the parameters of surgery (dose, conduit diameter) and factors such as age, weight, hemodynamic status, gives the surgeon essential information to achieve good results of a surgery.*

Keywords: *Data Mining, classification models, predictive models, neural networks, surgical efficiency.*

INTRODUCTION

Severity scoring models that can be used to predict patient deterioration, care outcomes and the likelihood of patient mortality in intensive care units have been developed for more than 30 years. Today it is a recognized classic and available tool for risk assessment and an indicator of the quality of hospital work.

In recent years, intelligent data processing technologies for various fields of medicine have been developed. In the early 2000s [1, 2], a new strategy for developing prognostic models using an ensemble of methods was introduced. By definition, ensemble methods are learning algorithms that build a set of classifiers and then classify a new data by weighted forecast voting. It has been shown that there are no "ideal methods" that work equally well on different databases.

Already, in 2011 researchers began to use a hybrid approach in order to achieve greater efficiency of solutions [3–6]. Such schemes and algorithms use a combination of different types of machine learning methods (classification and clustering) to select informative features and improve model performance. It has been demonstrated in various data that accuracy depends not only on the method but also on the set of classification features.

PROBLEM STATEMENT

In the Big Data era, decision tree methods, machine learning, neural networks, along with other Data Mining methods, became an alternative to classical statistical methods as a more useful tool for analyzing large and inhomogeneous data.

Decision tree methods, which were developed more than 20 years ago, have become widespread in medical research in the last decade. They are easily perceived by professionals in clinical practice, because they are clear and turn into logical conditions (decisive rules, classification rules). Previously, classification trees were used, for example, to calculate the probability of death from coronary pathology [7], intracerebral hemorrhage or traumatic brain injury [8], to predict Parkinson's symptoms [9], to assess the severity of the disease [10–12], to stratify patient groups by probability of mortality among the general population patients in intensive care [13–16].

Trujillano et al. [13] predicted the probability of hospital mortality using three decision tree classification algorithms: CART, CHAID and C4.5. All models are based on assessing the severity of patients during the first 24 hours after admission. The authors point out that the main advantages of decision trees are that the obtained decision-making rules can be easily interpreted, and the composition of the group of patients ("leaf" of the tree) obtained in each end node is relatively homogeneous.

In our previous studies, a method and information technology (IT) for classifying human health using a set of Data Mining methods based on objective and expert characteristics were developed [17, 18]. The use of IT to assess the disease activity of children with dysplasia made it possible to identify diagnostic markers of cardiovascular dysfunction and to develop diagnostic rules for determining the stages of the disease by ECG parameters (symmetry of the T wave, an integral indicator of the shape of the STT segment). The functional status and reliability of operators under conditions of intel-lectual load were also assessed. That made it possible to identify the most informative indicators of HRV, in which the changes of operators` reliability can be predicted, taking into account the type of autonomic regulation.

Note the intelligent support system for medical decision-making in intensive care units by the ensemble of classification models Data Mining — On-line knowledge discovery in the intensive care unit (INTCare), which is based on collecting data from bedside monitors and updating the model, which reduces the need for human intervention [16]. The system was used to predict organ failure (cardiovascular, coagulation, respiratory systems, liver and kidneys) and the treatment results of 129 patients (living or dead) of the Portuguese intensive care unit, based on the first five days of their stay. The system attributes were: monitor data, results of laboratory tests, systems of drugs and medical records. The predictive accuracy of the classification models ensemble varied from 43 % to 83 % (64 % to predict the outcome of treatment of an individual patient).

INTCare modeling and forecasting targets are survival and length of stay in bed. Note that the prognosis of patient length of stay (LOS) is considered as an indicator that helps to plan resuscitation resources and individualize patient care in the intensive care unit.

Two approaches were used to model and forecast these indicators. The first approach is to use data and physiological variables collected during the first 24 hours of inpatient treatment. The second approach used real-time patient clinical data.

The first approach achieved forecasting results with an accuracy of 73 %. However, when the duration of the stay was predicted using real-time data collected, efficiency increased (model sensitivity — 96.1 %). The following models were used: Support Vector Machine, Decision Trees, Naive Bayes. To predict survival, the Decision Trees method showed the best result (sensitivity — 87.3 %).

The most important feature of the intelligent decision support system INTCare is the ability to work autonomously and in real time. But such models, which are based on several measurements, are not designed to work with streaming data.

In recent years, in addition to decision trees [20], machine learning methods, artificial neural networks (ANN) [21], the method of support vectors machine (SVM) [22] have been increasingly used to verify and model the severity of patients. Intelligent systems for supporting hospital and diagnostic decisions with an accuracy of over 80 %

have been proposed [23–27]. Such systems use Data Mining methods and techniques. Once again, the advantage of decision trees is that they are clear and become logical conditions (classification rules).

Machine learning techniques can provide accurate predictions based on large data sets obtained from electronic medical records databases (EHRs). The most common goals of modern research are: predicting complications, mortality, length of hospital stay, improving health [27]. These authors have analyzed more than 150 articles on this subject and draw attention to the need of appling validation and verification procedures to avoid the risk of systematic modeling errors.

The conclusion concerning the possibility and usefulness of appling artificial intelligence methods for the evidence-based analysis of clinical data sets, the results of which are aimed at improving patient health, was made in 78 studies (2008–2018) in [29]. Such a study of analysis methods of clinical data stored in electronic medical records provide trustworthy evidence to support the decisions of health professionals.

Recently, there have been works that use *Deep Learning methods*, namely: Recurrent Neural Networks, neural networks with LSTM-blocks (Long Short-Term Memory) [30, 31]. It is demonstrated that predicting the patient's vital signs, using them to calculate the Prognostic Index and taking it into account in the treatment tactics development allows to predict future complications with high accuracy (> 80 %), which would be impossible using only the analysis of current vital signs patient: in 50 % – 60 % of cases, the probable deterioration of the patient's condition would not be detected [31].

Kwon J.M. [31] described a rapid response system for detecting and predicting cardiac death in a hospital. The system was developed as a deep learning-based early warning technology (DEWS). The DEWS system has a high sensitivity with a low error rate in detecting patients with in-hospital cardiac arrest. DEWS is easy to apply in different hospital settings, because it uses as input data time series of four vital signs. The DEWS artificial neural network consists of 3 recurrent layers with a short memory unit. For DEWS, the highest AUC ROC (Area Under the receiver operating Curve) values > 0,85 were obtained, which is higher than for the models of Logistic Regression, Random Forest and MEWS (Modified Early Warning Score), which is calculated according to six vital indicators [31].

Over the last fifteen years, another area of Data Mining has emerged — Mining symbolic time-intervals. Such methods use a subset of Allen time relations, KarmaLego algorithms and H-DFS (Hadoop Distributed File System) [33].

An example of such a development is Maitreya framework for the prediction of outcome events that leverages these symbolic time intervals. Symbolic elements based on clinical records are used as attributes: conditions, procedures, influence of hospital drugs. The Maitreya system uses the KarmaLego algorithm to form a complete set of templates named DharmaIndex [33]. It is argued that the use of this approach ("time pattern analysis") is more effective than other timeless methods.

Deep Neural Networks of different types have found application in cardiology for solving problems of diagnostics diseases, prediction cardovascular events [34, 35].

The most common tools for Data Mining and IT development are software products such as: SAS Data Mining [36], Statistica Data Mining [37], WEKA [38], RapidMiner [39], KNIME [40], Pyhton environment, R programming, among which are available, open source.

An example of such technology is the creation of predictive models of the critical patients` condition (survival) based on the integration of the clinical database MIMIC-II in the environment of Data Mining (RapidMiner) [41]. The RapidMiner platform supports scalable forecasting analytics according to the CRISP-DM standard process (CRoss-Industry Standard Process for Data Mining. RapidMiner) and with the help of visual tools (RapidMiner Radoop extension) allows to automate loading, data conversion, construction and evaluation of forecasting models according to various schemes function selection and parameter optimization. The authors concluded that prognostic analytics based on the accumulation of large amounts of medical data can stimulate the transformation of traditional medicine to prognostic, preventive and personalized medicine, which ultimately has a positive effect on both the cost and quality of care [41].

The Kong study [42] proposed a toolkit based on several machine learning methods (LASSO, RF, GBM, LR, implemented in the R environment) to predict in-hospital mortality in patients with sepsis. The efficiency of the developed models in comparison with the traditional SAPS II scale (Simplified acute physiology score). The MIMIC III clinical base was used for model training and validation. The advantage was shown by the GBM (Gradient Boosting Machine) model, which made it possible to identify a set of clinically significant variables that differ from those commonly used in practice (in the SAPS II scale).

The purpose of the paper is to indentify control parameters of the surgical intervention to optimize the EF ejection fraction after the surgery Data Mining method (neural networks).

ANALYSIS OF CHANGES IN PATIENTS' CONDITIONS AS A RESULT OF SURGICAL INTERVENTION

The study was conducted based on the results of surgery - implantation of conduit, in patients with severe heart defects. Conduit implant surgery is performed to treat severe heart defects such as aortic stenosis, aortic valve abnormalities (or left ventricular outflow obstruction). The success of the operation depends on many factors, among which the choice of the conduit parameters and the drug dose are important. We analyzed the database provided by a private clinic in the field of pediatric cardiac surgery (Kyiv). The database contained data of 79 children (aged from birth to 18 years).

Here are the studied indicators for the following blocks.

Anthropometric indicators: age of the patient (X1); weight (X2).

Hemodynamic (cardiac) parameters before surgery:

- end diastolic index (X3 — before surgery, X7 — after it);
- aortic pressure gradient (X4 — before surgery, X8 — after it);
- augmentation index (X5 — before the operation, X9 — after it);
- ejection fraction (X6 — before the operation, X10 — after it).

Characteristics of the studied indicators.

End diastolic index (EDI, ml/m^2) — the value of the end diastolic volume (EDV, ml) normalized by body surface area (BSA, m^2) :

$$X3 = EDV / BSA.$$

Aortic pressure gradient (Δ Pm), which in a healthy person ranges from 3 to 14 mm Hg, in a person with a mild form of aortic stenosis: 12–53 mm Hg.

Augmentation index (AI), reflects the level of compression of the vessel under the influence of external factors (high blood pressure, etc.). Its value reflects the endothelial dysfunction: a high AI index is a cardiovascular complications predictor, an indicator of subclinical atherosclerosis and the severity of left ventricular hypertrophy. Norm AI is 0,4–1,4.

The ejection fraction (EF) is a percentage of the blood ejected from the heart into the aorta during each contraction. Usually, at rest, a healthy heart throws out 50–70 % of the blood that is in it. In many people with heart failure, the ejection fraction is less than 40 %.

The analysis also includes data that are control parameters.

- Dopamine dose (U1). Dopamine is a cardiotonic agent that increases cardiac output and provides increased oxygen delivery.
- Conduit diameter (U2). Conduit is a widely used in clinical practice — surgical treatment of ascending aortic aneurysms, which is a synthetic corrugated vascular prosthesis of constant cross-section with a mechanical or biological valve.

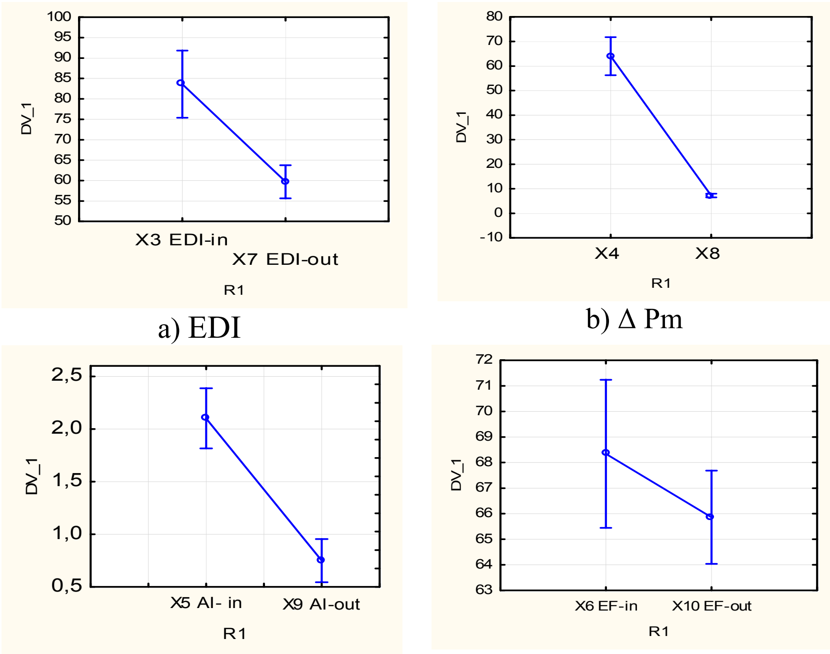
Descriptive statistics of all indicators are presented in table 1.

Analysis of changes in cardiac parameters. Changes in cardiac parameters after surgery were examined using the analysis of variance for repeated measurements (RepANOVA). It was determined that after the surgery there was a large, statistically significant decrease in 3 hemodynamic parameters — EDI, Δ Pm, AI, as well as some decrease in the average value of EF ($F(1,78) = 3,27$, $p = 0,07$) (Fig. 1, a-d).

Determination of typological groups according to the dynamics of the studied indicators. For in-depth analysis of the surgery effectiveness, a cluster analysis of data was performed to determine homogeneous groups. The *k*-means algorithm with 10-cross-validation is used, which allows to determine the optimal number of groups. The analysis was done on the basis of 4 hemodynamic parameters (before surgery). Three clusters are defined; cluster centers profiles are given in Figure 2.

Table 1. **Indicators descriptive statistics**

Model indicators	Mean	Minimum	Maximum	Std.Dev.
X1	119,10	0,67	216,63	66,67
X2	35,99	3,3	94	21,05
X3	83,62	32	211	36,71
X4	63,97	9	177	34,54
X5	2,10	0	4	1,27
X6	68,34	10	88	12,92
U1	302,68	137,5	488	89,89
U2	23,43	14	32	3,41
X7	59,73	22	133	18,10
X8	7,25	1	17	3,38
X9	0,75	0	5	0,92
X10	65,86	30	78	8,14



a) EDI b) Δ Pm c) AI d) EF

Fig. 1. Average values of cardiac parameters before and after surgery

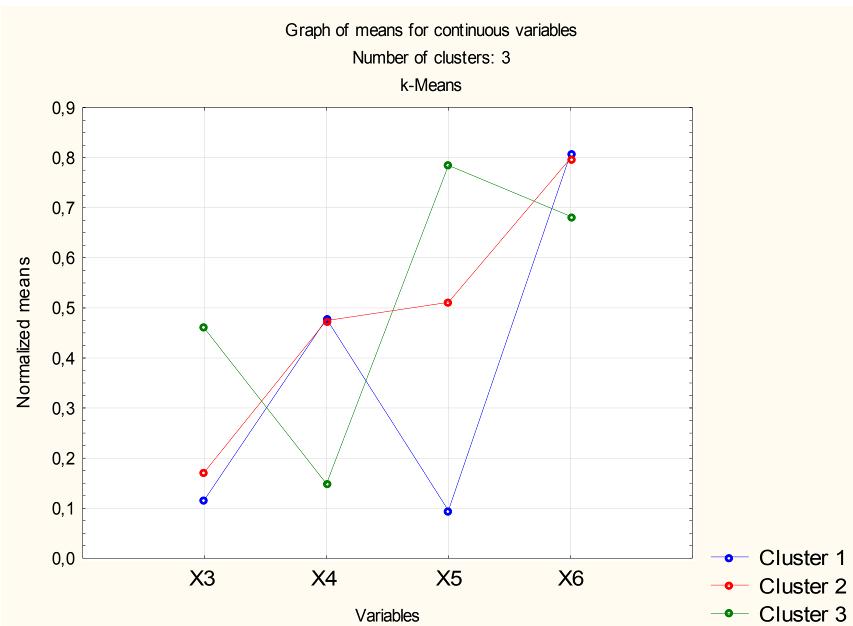
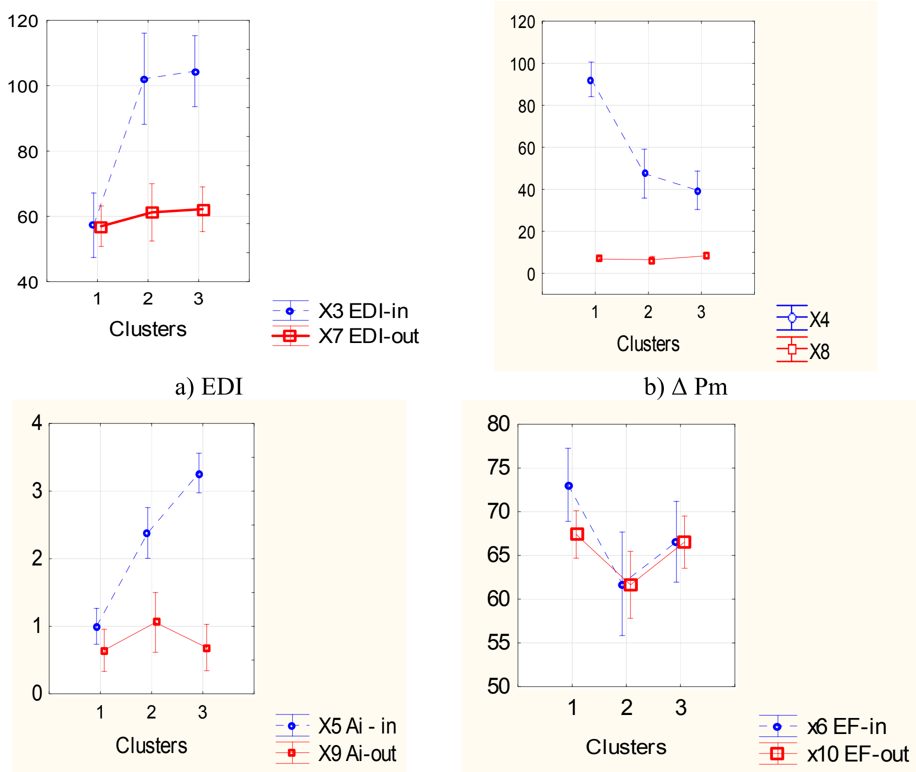


Fig. 2. Profiles of selected three clusters (groups)



a) EDI b) Δ Pm

c) AI d) EF

Fig. 3. Comparison of hemodynamic parameters in the three groups before (dashed line) and after (continuous line) surgery

Clusters differ significantly in all studied hemodynamic parameters. The following differences were found between the three identified groups of children.

Group 1 (cluster 1) included 34 children, average age 156 months (senior group). Feature of group 1: in children the lowest values of EDI are accompanied by the highest values of the pressure gradient on the aorta.

Group 2 (cluster 2) consists of 17 babies, the youngest aged — 28.2 months.

Group 3 (cluster 3) included 28 children aged 79 to 204 months, in whom the augmentation index was the highest.

An analysis of hemodynamic parameters changes in certain groups after surgery was performed (Fig. 3, a-d). The results of the analysis (Fig. 3) show that in all groups there is a large, statistically significant decrease in indicators and preservation of the level of PV, which was the purpose of the surgery. Only in the older group of children (cluster 1) with low EDI there is a slight but statistically significant decrease in EF: from 73,0 % to 67,4 %: $F(1, 33) = 10{,}055$, $p = 0{,}00327$.

CONSTRUCTION OF MODELS FOR PREDICTING THE PATIENT'S CONDITION AS A RESULT OF SURGERY

It is known that artificial neural networks can be used not only for recognition, classification, but also for predicting functional dependencies. That is, neural networks can reveal hidden dependencies, relationships between the input data and the target variable. And then, based on this predictive function, management decisions can be made.

One of the main problems of such modeling is the choice of the neural network model type. Given the peculiarities of the task — the prediction of the values of the many variables function, we chosen a neural network type RBF (with radial-based activation functions). The mathematical basis for choosing such a model is the statement that arbitrarily accurate approximation of functions is achieved by a combination of radially symmetric functions.

Traditionally, the term RBF network is associated with radially symmetric functions in single-layer networks that have the structure shown in Figure 4.

Define the input data vector as X. Each of the n components of the input vector is fed to the neural network input with consists of m neurons. The output of the RBF network is a linear combination of a basic functionsset

$$f(X) = \sum_{j=1}^{m} w_j h_j(X),$$

where w_j is weight j-neuron connection, $h_j(X)$ is the neuron activation function is radially symmetric, in our case it is a Gaussian function:

$$h(X) = \exp(-\frac{\|X-c\|^2}{r^2}),$$

where c is bias coefficient, r is range parameter.

The models were built using the Data Mining Automated Neural Networks module of the STATISTICA package. This module provides the ability to automatically search for the best neural network, allows you to configure the following learning parameters: network type (radial-based functions or multilayer perceptron), activation function, minimum and maximum number of neurons in the hidden layer, error function and others. That is, it is possible to adjust the complexity of the neural network, to control the parameters that affect the quality of the model, as well as the ability to import the resulting neural network in various programming languages such as Java or C +.

In network training, the task is to optimize the system parameters according to the selected criteria. Such a criterion, in particular, may be the criterion of the minimum mean square of the error on the learning set ($E(w)$):

$$E(w) = \frac{1}{p}\sum_{i=1}^{p}(y_i - d_i)^2,$$

where y_i - is the value of the j-th output of the neural network, d_i is the target value of the i-th output, p is the number of neurons in the final layer.

Table 2. **Performance indicators of the selected model**

Net. name	**Training perf.**	**Test perf.**	**Validation perf.**	**Training error**	**Test error**	**Validation error**	**Training algorithm**	**Error function**
RBF 2-7-1	0,42	0,44	0,47	30,3	21,9	15,5	RBFT	SOS

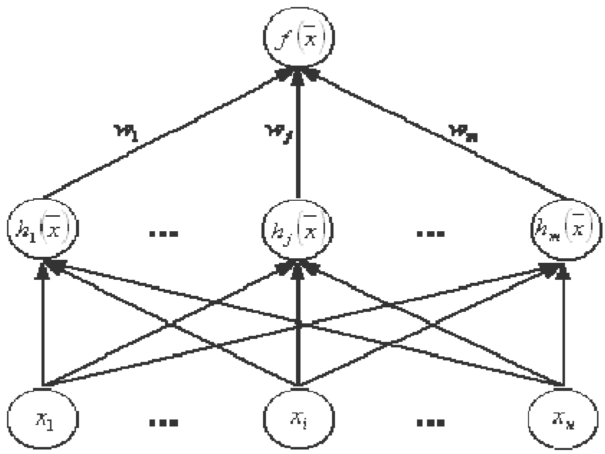


Fig. 4. The structure of the RBF neural network

Neural network learning outcomes. The entire data sample was divided into three parts: training — 75 %, control — 15 %, test (for validation) —15 %. The criterion for selecting models is the minimization of the error function (SOS — the sum of squares of errors).

Automated search — training of the neural network under the conditions of initial selection (minimum number of neurons in the intermediate layer — 5, maximum — 16), enables to determine model of 7 neurons as the best one (table 2).

The parameters of the neural network model 2- RBF-2-7-1 are shown in the table 3.

Prediction of control parameters in surgical intervention to optimize the ejection fraction values. In the first step, the regression dependence of EF after surgery on the control parameters (model 2- RBF-2-7-1) have been ditermined, namely: conduit diameter and dopamine dose, the surface of the three-dimensional graph has a maximum (optimal value) EF, which depends on the diameter of the conduit and the dose of dopamine (Fig. 5). Visual analysis shows that the surface of the three-dimensional graph has a maximum of more than 70 % EF, which depends on the dopamine dose and the conduit diameter. The forecast of EF value was calculated for arbitrary values of control parameters that changed in ascending order in the given ranges (Table 4).

According to this model, the optimal value of EF — 70,7 %, can be obtained under the following conditions: dopamine dose — 280 ml and conduit diameter — 22 mm. Note that for this neural network, under the condition of a constant level of the parameter U1 (dopamine) and an increase in U2 (diameter of the conduit), the level of EF increases (see Fig. 5). Therefore, there is no global maxim for all possible values of control parameters in this model.

In order to improve the forecasting results, model studies were done to identify other possible predictors to achieve the maximum level of EFout (target function) and a number of possible predictors were identified (Table 5, the best predictors are sorted by F-criterion value).

Therefore, in addition to the control parameters U1, U2 (dopamine dose, conduit diameter), which were selected by experts and taken into account in the 2- RBF-2-7-1 model, the ejection fraction before surgery (EF-in, X6) can be predictors of EFout, as well as the child's weight -X2.

Table 3. **Neural network parameters for 3- RBF-2-7-1. (дати анг назви)**

N	Connections	Weight values
1	U1 dopamine dose --> hidden neuron 1	0,001912
2	U2 conduit diam.--> hidden neuron 1	0000
3	U1 dopamine dose --> hidden neuron 2	0,694722
4	U2 conduit diam.--> hidden neuron 2	0,388889
5	U1 dopamine dose --> hidden neuron 3	0,340086
6	U2 conduit diam.--> hidden neuron 3	0,500000
7	U1 dopamine dose --> hidden neuron 4	0,774608
8	U2 conduit diam.--> hidden neuron 4	0,555556
9	U1 dopamine dose --> hidden neuron 5	0,306705
10	U2 conduit diam.--> hidden neuron 5	0,666667
11	U1 dopamine dose --> hidden neuron 6	0,326676
12	U2 conduit diam.--> hidden neuron 6	0,888889
13	U1 dopamine dose --> hidden neuron 7	0,266762
14	U2 conduit diam.--> hidden neuron 7	0,333333
15	radial spread hidden neuron 1	0,425743
16	radial spread hidden neuron 2	0,184823
17	radial spread hidden neuron 3	0,169977
18	radial spread hidden neuron 4	0,184823
19	radial spread hidden neuron 5	0,169977
20	radial spread hidden neuron 6	0,223118
21	radial spread hidden neuron 7	0,182083
22	hidden neuron 1 --> X10 EF-out	0,035833
23	hidden neuron 2 --> X10 EF-out	0,013107
24	hidden neuron 3 --> X10 EF-out	0,069697
25	hidden neuron 4 --> X10 EF-out	0,017845
26	hidden neuron 5 --> X10 EF-out	-0,064549
27	hidden neuron 6 --> X10 EF-out	0,168681
28	hidden neuron 7 --> X10 EF-out	-0,011007
29	hidden bias --> X10 EF-out	0,561705

Modification of the model taking into account additional predictors. After training the model with 4 input variables based on radial functions, a neural network (index 3) with the number of neurons 7 was selected, which is denoted by RBF 4-7-1 (Table 6). Note that the model's performance was better in the training and test samples than in other models with the same number of neurons, and the validation error was smaller than in the previous model with two input variables — RBF 2-7-1.

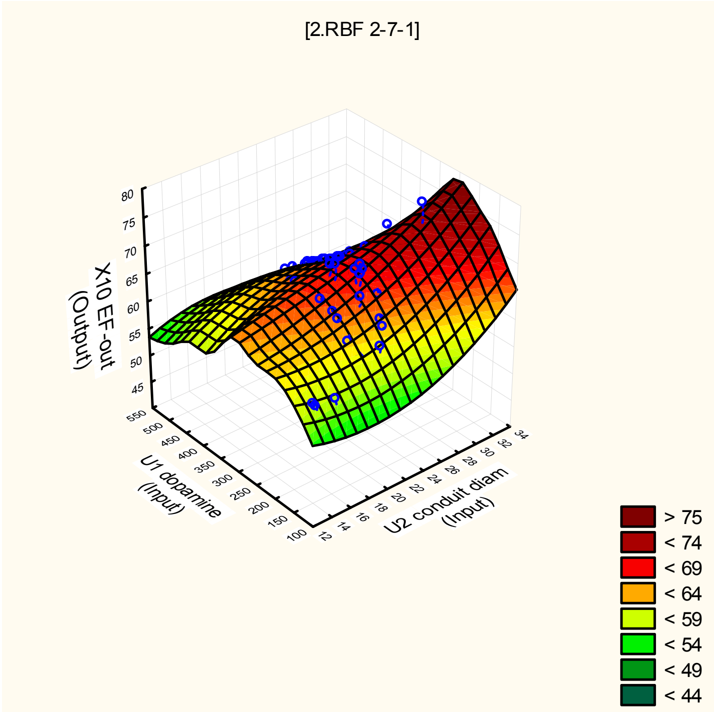


Fig. 5. Three-dimensional graph of the model 2-RBF-2-7-1 for forecasting the fraction of PV emissions after surgery, points on the surface — real data

Table 4. **Forecasted values of the emission fraction calculated according to the model in case of control parameters change**

№№ forecast option	2.X10 -EF out_(t)	U1 dopamine	U2 conduit diam
1	58,3	140	15
2	59,4	160	20
3	60,6	180	20
4	62,1	200	20
5	66,9	220	22
6	69,0	240	22
7	**70,7**	**280**	**22**
8	69,9	300	24
9	69,1	320	24
10	67,6	340	26
11	66,8	360	30
12	58,0	250	15

Table 5. **Indicators — the best predictors of EF after surgery**

EFout predictors	F-value	p-value
X7 EDI-out	8,167062	0,00001
X6 EF -in	7,682503	0,0002
X2 weight	3,795432	0,001490
U1 dopamine dose	2,434001	0,022043
U2 conduit diameter	2,190949	0,032986

Table 6. **Performance indicators of the RBF 4-7-1 model in neural network training**

Index	Net. name	Training perf.	Test perf.	Validation perf.	Training error	Test error	Validation error	Training algo-rithm	Error function
2	RBF 4-7-1	0,34	0,65	0,68	33,26	14,65	10,62	RBFT	SOS
3	**RBF 4-7-1**	0,50	0,47	0,59	27,47	25,84	13,02	RBFT	SOS
4	RBF 4-7-1	0,42	0,61	0,61	30,02	16,43	11,99	RBFT	SOS
5	RBF 4-16-1	0,60	0,33	0,61	23,43	27,37	12,79	RBFT	SOS
6	RBF 4-16-1	0,56	0,16	0,60	25,16	29,58	12,86	RBFT	SOS

The model with index 3 RBF 4-7-1 has 4 input variables and consists of seven neurons. Figure 6 shows graphs of the calculated surface of the dependence of EF values after surgery on the diameter of the conduit and dopamine. The marks in Figure 6 are the same as in Figure 5.

As can be seen from Figure 6 three-dimensional surface, calculated on the neural network 3- RBF-4-7-1, has a global maximum at the level of EF > 65 %.

More concrete results can be obtained if we approximate the dependences of EF on control parameters, taking into account their real values and calculated by the neural network. In Figure 7 shows such comparisons of dependences, which are approximated by polynomials (red line — values calculated by the neural network and blue line — real data).

By analyzing the data and calculations of the EFdependence on the conduit diameter (Fig. 7a) and the dopamine dose of (Fig. 7b), we can conclude that to achieve maximum EF (more 65 %) after the surgery there are the following optimal values of control parameters: conduit diameter — 20–26 mm, dopamine dose — 250–350 ml., depending on weight (age) child.

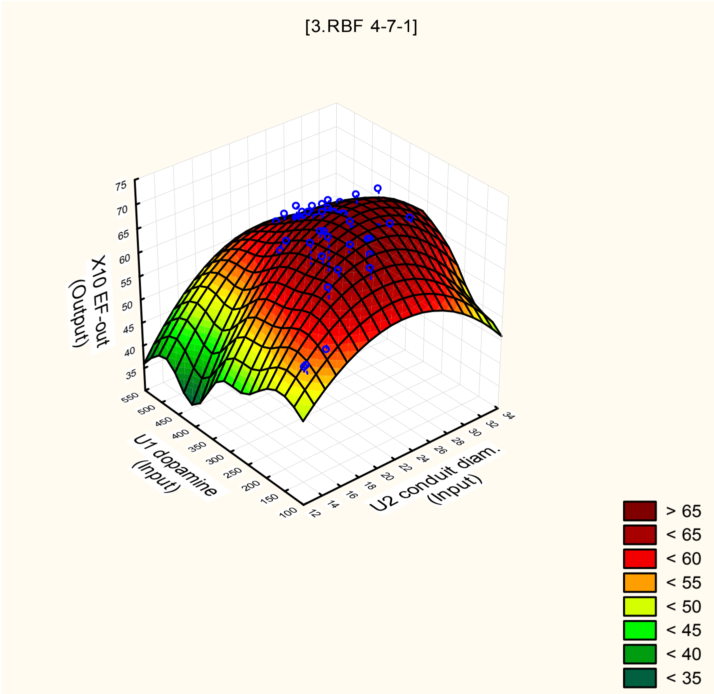
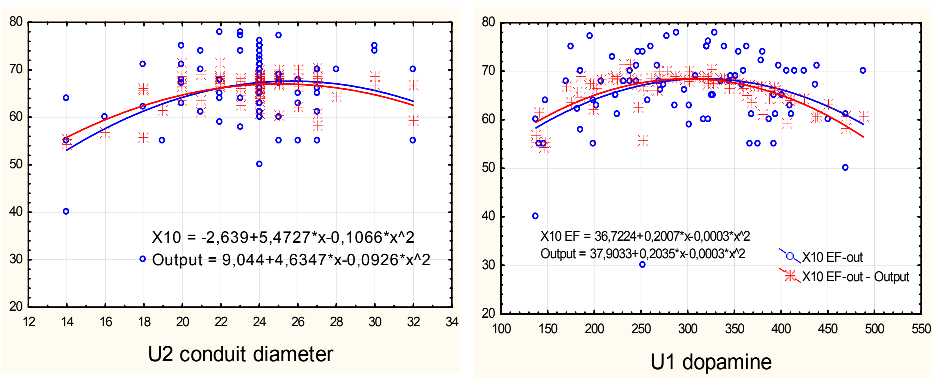


Fig. 6. Three-dimensional graph of EF dependence on 4 input parameters, calculated on the neural network 3- RBF-4-7-1



a) b)

Fig. 7. Graphs of dependence of EF on the conduit diameter (a) and on the dopamine dose (b) (real data — blue and model — red)

Thus, with the help of the developed model it is possible to predict obtaining a satisfactory result according to the target indicator — the value of EF after surgery, using the input data: child's weight, EF before surgery, conduit diameter, dopamine dose.

CONCLUSIONS

A retrospective analysis of changes in the children cardiac parameters after surgery showed the expected changes in clinically significant indicators (decrease in the aortic pressure gradient and augmentation index). But the average value of the emission fraction after cardiac surgery has slightly decreased, although the main goal of the operation is to keep it at a level of at least 65 %.

The cluster analysis revealed three subgroups of children who differed in hemodynamic parameters before the surgery. In addition, these groups were distinct in age and weight. A subgroup of older children was identified in whom the effectiveness of the operation was somewhat unsatisfactory, as after the surgery the emission fraction values decreased statistically significantly.

The use of predictive models developed by the type of RBF neural network with radially symmetric functions in single-layer networks, allowed to analyze the surgical interventions effectiveness in the case of congenital heart disease in infants and children. Taking into account the results of the developed predictive model of the dependence of the cardiac output fraction on the control surgery parameters of dopamine dose, conduit diameter and factors such as age, weight, hemodynamic status, gives the surgeon essential information to make a more effective decision on the choice of control parameters.

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ПРОГНОЗУВАННЯ КЕРУВАЛЬНИХ ПАРАМЕТРІВ ОПЕРАЦІЙНОГО ВТРУЧАННЯ У КАРДІОЛОГІЇ ДЛЯ ОПТИМІЗАЦІЇ ЗНАЧЕНЬ ФРАКЦІЇ ВИКИДУ ЗА ДОПОМОГОЮ НЕЙРОМЕРЕЖІ

Вступ. В епоху Big Data методи дерев рішень, машинного навчання, нейронних мереж разом з іншими методами Data Mining стали альтернативою класичним статистичним методам як корисніший інструмент для аналізу великих та неоднорідних даних. Методи нейронних мереж стали точнішими та ефективнішими технологіями вирішення широкого спектру медичних проблем, таких як діагностика, прогнозування, лікування.

Мета роботи — визначити контрольні параметри хірургічного втручання для оптимізації фракції викиду після операції за допомогою моделей методу Data Mining (нейронної мережі).

Результати. Здійснено аналіз змін гемодинамічних показників стану дітей з тяжкими вадами серця внаслідок хірургічного втручання - вживлення кондуїту. Проаналізавано зміни цих показників після операції за допомогою дисперсійного аналізу для повторних вимірювань (RepANOVA). Визначено, що після операції спостерігалося значне, статистично значиме зменшення 3-х гемодинамічних показників — КДІ, Гр, АІ. За кластерним аналізом визначено три групи пацієнтів, які відрізнялись за всіма гемодинамічними показниками та за особливостями зміни досліджуваних показників після операційного втручання. Побудовано модель на основі нейромережі типу RBF (з радіально-базисними функціями активації) з використанням модулю Data Mining Automated Neural Networks пакету STATISTICA.

За розробленими моделями визначено залежність фракції викиду після операції від параметрів керування — дози допаміну та діаметру кондуїта. Встановлно, що модель нейронної мережі, яка додатково враховує вагу дитини та початковий рівень фракції викиду, має більшу продуктивність.

Висновки. Застосування прогнозних моделей нейромереж, розроблених за типом RBF мережі з радіально-симетричними функціями в одношарових мережах, дало змогу проаналізувати результативність операційних втручань у разі вроджених вад серця у немовлят та дітей. Врахування результатів застосування розробленої моделі залежності фракції серцевого викиду від параметрів операційного втручання (доза препарату, діаметр кондуїту) та таких факторів як вік, вага дитини, стан гемодинаміки, дає хірургу суттєву інформацію для прийняття ефективнішого рішення про головні керувальні параметри**.**

Ключові слова**:** *класифікаційні моделі Data Mining, прогнозні моделі, нейромережі, ефективність хірургічного втручання.*