Machine Learning Models for Atrial Fibrillation Prediction after Coronary Artery Bypass Graft Surgery

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Abstract

The primary objective was the comparative quality metrics analysis of multivariate logistic regression, stochastic gradient boosting and an artificial neural network models with continuous and boundary-binarized preoperational factors for patients with new-onset atrial fibrillation prediction after coronary artery bypass graft surgery.

Keywords
Predictive models, stochastic-gradient boosting, artificial neural network, features selection, post-operational fibrillation.

1. Introduction

Artificial intelligence (AI) technologies implementation allows quality improvements in various clinical medicine areas, particularly medical care by diagnostic capabilities expansion and predictive assessments improving. In cardiac surgery, for instance, various prognostic scales are being developed based on machine learning algorithms and other data mining methods to assess patients' individual risk, minimize the likehood of postoperative complications and to optimize treatment strategy.

One of the most frequent cardiac surgery practice complications is postoperative atrial fibrillation (POAF), which, depending on the type of surgery is observed in 25-40% of patients [1, 2]. Recent papers for atrial fibrillation (AF) prediction shows the effectiveness of artificial neural networks in development of accurate predictive models in patients with coronary heart disease (CAD) using machine learning methods. Sidrah Liaqat et al. [3] developed a convolutional neural network with quality metric area under the ROC curve (AUC) equal to 0.81, LSTM (AUC - 0.83) and convolutional LSTM (AUC - 0.80). Hill N.R. et al. [4] create neural network model with AUC 0.83, based on electrocardiography (ECG) data. Yong Xia et al. [5] obtained a convolutional neural network model with a sensitivity of 98.34%, a specificity of 98.24% and an accuracy of 98.29%. Lown M. et al. [6] created an SVM model with a sensitivity of 99.2% and a specificity of 99.5%.

The POAF risk measurement is highly important in cardiac surgery. Its occurrence after coronary artery bypass grafting (CABG) increases the risk of stroke, postoperative bleeding and acute renal failure by 4 times and doubles the probability of 30-days and 6-month horizons mortality [1, 7]. Despite large number of studies, until now there is no single pathophysiological concept that describes detailed

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mechanisms of AF development and no unified scale for its occurrence risk calculation after CABG. However, there are small number of studies describing the binary classification methods (logistic regression (LR), random forest method (RF), decision trees and multilayer perceptron) in predictors identification and prognostic model's development tasks [8, 9]. For instance, study by Mathew J.P. et al. [10] describes the accuracy of the logistic regression (LR) model according to the AUC metric around 0.7. The dataset included 1503 patients with CAD after CABG and determined the following parameters as predictors: age, AF history in the preoperative period, history of heart valve surgery, postoperative withdrawal of β-blockers and angiotensin-converting enzyme inhibitors. In a retrospective study, Güngör et al. [11] on the data of 125 patients obtained LR model, describing patients age and platelet-lymphocyte index as predictors. The model accuracy according to the AUC metric was 0.634, and the sensitivity and specificity were 64% and 56%, respectively. In a study by Magee M.J. et al. [12] the developed LR-model included 14 factors (AUC 0.72). The most significant predictors were preoperative and intraoperative factors: patients age, prolonged mechanical ventilation (24 hours or more), presence of cardiopulmonary bypass, and supraventricular arrhythmias history. Zaman A.G. et al. [13] during analysis of 326 patient's data (among whom the AF was observed in 92) with LR identified the following predictors: patients age (> 75 years), increased duration of the P wave (> 155ms) and male sex and developed AF prediction model with sensitivity and specificity in 49% and 84%, respectively. Amaret et al. [14] using stepwise LR developed a model with an AUC of 0.69, which included the following factors: sum of filtered signals from 3 orthogonal ECG leads before surgery, the patients elderly age and male gender. Todorov et al. [15] on a sample of 999 patients developed a multivariate model of AF prediction with AUC 0.68 and identified the following pre- and postoperative predictors: duration of mechanical ventilation and time spent in the intensive care unit, elderly age, increased C-reactive protein and plasma creatinine concentration. To predict POAF after CABG, many researchers used the prognostic scales EuroSCORE [16], Kolec [17], PAFAC (Predictors of AF After CABG) [18], CHA2DS2-VASc and HAS-BLED, calculated using LR, showing the accuracy AUC metric from 0.65 to 0.68 [19, 20].

Thus, recent studies indicate a high accuracy in predicting AF in patients with coronary artery disease, but insufficient accuracy of previously developed models for predicting new-onset POAF after CABG, which prompted authors to analyze this problem more deeply. The aim of the study is to develop and improve the algorithm for POAF predictors selection and prediction models development for patients with CAD after CABG.

2. Materials and methods

The development of models was carried out based on data from a retrospective study containing electronic medical records (EMR) of 886 CAD patients (181 women and 685 men) aged 35 to 81 years with a median of 63 years and a 95% confidence interval (CI) [63; 64], who underwent isolated CABG under cardiopulmonary bypass in the period from 2008 to 2019 in cardiac surgery department of the Primorsky Regional Clinical Hospital No. 1, Vladivostok. Patients with any history of AF were excluded from the study. The total number of such patients was 85. Thus, the dataset was presented by the examination results of 801 patients with coronary artery disease. Verification of POAF was carried out according to the results of ECG monitoring for at least 96 hours after CABG. Among the surveyed cohort, 2 groups of patients were identified. The first included 153 (19.1%) patients with recorded AF paroxysms in the postoperative period, the second - 648 (80.9%) patients without cardiac arrhythmias. In the first group, hospital mortality was 9.8% (15 patients), and in the second - 4.6% (30 patients).

The end point of the study was POAF in the form of a categorical binary feature ("absence" or "development"). Input attributes - a subset of 100 potential predictors was expressed in the form of continuous and categorical variables. Methods of statistical analysis and machine learning were used for data processing and analysis. The first of them were presented by Chi-square, Fisher, Mann-Whitney tests and univariate LR with the calculation of weight coefficients. The second - by multivariate LR, stochastic gradient boosting (SGB) and artificial neural network (ANN). The architecture of ANN was the multilayer perceptron selected by maximizing the area under the ROC curve (AUC) and consisted of the two hidden layers of 90 and 80 neurons each. "Sigmoid" and "relu" were used as the ANN activation function. In the final models, taking into account the best accuracy of the ANN, only the “sigmoid” function was included. The accuracy of the models was assessed according to 4 quality metrics: AUC, sensitivity (Sen), specificity (Spec), and accuracy (Acc). Model development included a k-box cross-validation procedure. The models were built on training sample (9/10) of patients and verified on test sample (1/10). All quality metrics values given in this work were obtained by averaging the forecast estimates on test samples.

The study design included 4 stages. Firstly, statistical analysis was used, with the help of which intergroup potential POAF predictors comparisons were carried out. Since preliminary assessment of the data closeness to the normal distribution by the Shapiro-Wilk method showed a negative result, for continuous variables the Mann-Whitney test was used. The chi-square test was used to compare categorical variables, and the Fisher test was used to assess the odds ratio (OR) and their CI. Secondly, using methods mentioned above, the boundaries of analyzed factors values with the best predictive potential were determined. This procedure included testing hypotheses about the equality of feature distributions in comparison groups. The selection of prognostically significant ranges was carried out with a testing step of 0.05-0.1 conv. units for various indicators. The selection criteria corresponded to the boundaries of the values of the factors, the p-value of which had the minimum, and the OR - the maximum value. At the third stage, the weight coefficients corresponding to the significance influence of individual POAF development traits were determined using standardized characteristics of univariate LR. At the fourth stage, multivariate models based on LR, SGB and ANN were developed, the structure of which was step by step supplemented with potential POAF predictors and quality metrics assessment. With an increase in the values of the latter, it was assumed that the indicator included in the model can be considered as a predictor of POAF. Data processing and analysis were carried out with R in the R-studio environment and in Python using the keras, tensorflow and xgboost packages.

3. Results

Comparative intergroup (between patients with and without POAF) factors analysis characterized the preoperative clinical and functional state of patients after CABG showed that reliably significant intergroup differences were recorded only for 10 indicators: age; compound parts of the electrocardiograms - PQ and QRS segment, RR interval and QT duration; echocardiographic parameters of the heart - upper-lower (LA3) and transverse (LA2) dimensions of the left atrium (LA), longitudinal (RA1) and transverse (RA2) dimensions of the right atrium (RA), end systolic dimension (ESD) of the left ventricle (LV); a history of tricuspid valve insufficiency (TVI); ejection fraction (EF) of LV blood during systole (Table 1).

The largest statistically significant intergroup difference (between patients with and without POAF) was observed in the following factors: RA1, RA2 and the duration of the QT interval (p-value <0.0001). Relative to patients without arrhythmia, in POAF group LA indices (LA2, LA3) were significantly higher alongside with statistically significantly shorter QRS duration. Further analysis showed that the pairwise product of indicators LA2 and LA3, alongside with RA1 and RA2 shows a statistically higher level of intergroup differences significance then assessment effect of individual heart chambers geometric parameters. Less noticeable, but statistically significant differences for patients with postoperative arrhythmia were associated with older age, higher LV ESD, QRS interval duration and TVI presence.

Table 1
Patients clinical and functional characteristics

Factors	Sample size	1 group, n=153	2 group, n= 648	p-value
Age, years	801	64 [63; 66]	63[62; 64]	0,00076

EF,%	783	59 [57;60]	60[60; 60]	0,039
LA2, mm	734	41 [40; 42]	39 [39; 40]	0,026
LA3, mm	734	38 [37; 39]	37 [36; 37]	0,013
LA2 * LA3, mm^2	734	160 [147; 168]	144 [141; 148]	0,011
RA1, mm	734	39,5 [3,9; 40]	37 [36; 37]	0,00007
RA2, mm	734	43 [41; 43]	39 [38; 40]	0,00003
RA1 * RA2, mm^2	734	164[160; 176]	144 [140;148]	0,000012
PQ, ms	801	160 [150; 160]	150[140; 150]	0,1
QRS, ms	801	80[80; 100]	100[80; 100]	0,0019
RR, ms	761	936,5[909; 1000]	920[882,4; 950]	0,22
QT, ms	761	400 [400; 410]	400[380; 400]	0,00012
ESD LV, mm	733	350 [330; 360]	340[330; 350]	0,037
TVI, abs (%)	801	34 (22,2%)	79 (12,2%)	0,002

At the second stage of the study, among the indicators with significant differences in the comparison groups, the ranges of their values with the highest predictive potential were verified (Table 2). The following boundaries of continuous factors were identified that have a statistically significant effect on the development of POAF: men age over 55 and under 75 and women over 60 and under 79 (OR = 3.4, $p < 0.0001$); PQ segment duration more than 160 and less than 200 ms (OR = 2.2, p = 0.0004), QRS depolarization complex more than 50 and less than 100 ms (OR = 1.5, p = 0.021), RR interval ranges from 1000 to 1100 ms, QT greater than 420 ms alongside with echocardiography hearth parameters: multiplication of LA3 and LA2 more than 150 mm2, multiplication of RA1 and RA2 more than 160 mm^2/ Moreover, LV ESD more than 4.9 cm shows a 2.9-fold increase in risk and EF more than 45 and less than 60% increased the risk of POAF by 1.7 times (p = 0.0058). The procedure for finding the boundaries of continuous variables made it possible to identify not only significant ranges of predictors and thus determine risk factors, but also to identify additional predictors that had not previously been verified as such (PQ and RR).

Table 2

POAF risk factors with the best predictive potential values boundaries

Predictor and Its Boundary	1 group, n=153	2 group, n= 648	OR, 95% CI	p-value
Age, years M 55- 74 F 60-78	142 (92,8 %)	511 (78,9%)	3,4 [1,9; 6,9]	0,0001
EF,% 45-60%	81 (52,9%)	268 (41,4%)	1,68[1,17; 2,42]	0,0058
ESD > 490 mm	7 (4,6%)	11 (1,7%)	2,9 [1,05; 7,7]]	0,049
LA2*LA3 >160 mm2	67 (43,8%)	191 (29,5%)	2,1 [1,4; 3]	0,0002
RA1 * RA2 >150 mm^2	92 (60%)	269 (41,5%)	2,5[1,7; 3,8]	<0,0001
PQ 170-210 ms	38 (24,8%)	47 (7,3%)	2,2 [2,6; 6,8]	0,0004
QRS 50-80 ms	88 (57,5%)	303 (46,8%)	1,53 [2,2; 14,4]	0,021
RR 1000-1100 ms	70 (45,8 %)	175 (27%)	2 [1,4; 2,9]	0,00033
QT, ms M>420 ms F>440 ms	45 (30,8%)	100 (16,3%)	2,3 [1,5; 3,5]	0,00013
TVI, abs (%)	34 (22,2%)	79 (12,2%)	2 [1,3; 3,2]	0,002

Remark: M – males; F – females

During third stage of the study univariate LR models were developed with weight coefficients calculation for characterization of analyzed indicators predictive values and verification of possible risk factors interrelationships alongside with the likelihood of POAF (Table 3). This approach allowed to assess more detailed potential predictors influence on the resulting variable. Age, QRS and PQ segments shows the greatest influence on POAF.

Table 3
Weights for POAF risk assessment univariate LR models

Factors	Coefficient	p-value
Age, years M 55- 74 F 60-78	1,24	0,00015
EF: 45 - 60%	0,42	0,03
LA2*LA3 >160 mm^2	0,73	0,00016
ESD LV > 490 mm	1,07	0,03
RA1 * RA2 >150 mm^2	0,94	<0,0001
PQ 170 - 210 ms	1,44	<0,0001
QRS 50-80 ms	1,63	0,0005
RR 1000- 1100 ms	0,87	<0,0001
QT, ms M>420 ms F>440 ms	0,78	0,00016
TVI, abs (%)	0,72	0,0016

At the fourth stage of the study, using the step-by-step inclusion of predictors in continuous or categorical form LR (Table 3), SGB (Table 4) and ANN (Table 5) models were developed. One of the objectives for our study was assessing the effectiveness categorical form predictors usage in comparison with their continuous counterparts. Accuracy increase of multivariate LR models was recorded in models 2-7 (Table 4). The maximum accuracy according to the Sen metric (0.67) was achieved in models 6 and 7 with AUC 0.71 and 0.7, respectively. The Spec level was 0.66. Further expansion of possible predictors lowered the Sen metric while retaining the levels of other metrics. This fact indicated that such parameters as ESD, EF and TVI are related, possibly linearly, with indicators of atrial size, ECG data and age. Analysis of LR-based models using categorical variables (models 11-20 in Table 4) showed that the accuracy of the models improved similarly to the continuous case, but it could achieve better values. For example, a comparison of models 7 and 17 shows that the latter has the best accuracy for all 4-quality metrics (0.69 vs 0.67, 0.71 vs 0.66, 0.74 vs 0.7 and 0.71 vs 0.67). Further expansion of the categorical predictors of models 18-20 did not significantly change the forecast accuracy.

Table 4
POAF predictive models accuracy assessment on test samples for multivariate LR

N	Predictors	Predictor and Its Boundary	Accuracy metrics			
			Sen	Spec	AUC	ACC
1	Age	-	0.46	0.63	0.58	0.59
2	Age, PQ	-	0.51	0.62	0.59	0.6
3	Age, PQ, QRS	-	0.6	0.6	0.62	0.6
4	Age, PQ, QRS, RR	-	0.56	0.61	0.63	0.6
5	Age, PQ, QRS, RR, QT	-	0.62	0.61	0.67	0.61
6	Age, PQ, QRS, RR, QT, RA1*RA2	-	0.67	0.66	0.71	0.66
7	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3	-	0.67	0.66	0.7	0.67
8	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD	-	0.64	0.68	0.71	0.66
9	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF	-	0.62	0.68	0.7	0.66
10	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF, TVI	-	0.58	0.7	0.7	0.68
11	Age	M 55- 74 Ж 60-78	0.93	0.21	0.57	0.35
12	Age + PQ	170-210 ms	0.25	0.93	0.64	0.8
13	Age, PQ + QRS	50-80 ms	0.72	0.46	0.66	0.5
14	Age, PQ, QRS + RR	1000-1100 ms	0.56	0.75	0.7	0.71

15	Age, PQ, QRS, RR + QT	M>420 ms Ж>440 ms	0.67	0.69	0.72	0.69
16	Age, PQ, QRS, RR, QT + RA1*RA2	> 160 mm^2	0.63	0.74	0.75	0.72
17	Age, PQ, QRS, RR, QT, RA1*RA2 + LA1*LA2	> 150 mm^2	0.69	0.71	0.74	0.71
18	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3 + ESD	>490 mm	0.68	0.71	0.75	0.71
19	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD + EF	45-60%	0.68	0.72	0.75	0.71
20	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF, TVI	-	0.69	0.71	0.75	0.71

Models based on SGB were developed in a similar way (Table 5). Predictive assessment accuracy increase was recorded in 2-5 SGB models. The 4-quality metrics obtained in the 5th model are currently the best predictive estimates in comparison with all previously published results: 0.82, 0.76, 0.77 and 0.76 for AUC, ACC, Sen and Spec, respectively. Further inclusion of statistically significant predictors in the SGB-based models in a continuous form reduced the quality of the prediction (models 6-10). Models of SGB 11-20, developed using predictors in categorical form, reached peak accuracy with the same set of indicators as the LR model (models 17 in Tables 4 and 5). Further expansion of the categorical predictors range didn't lead to prediction quality changes Models based on LR and SGB were comparable in terms of the accuracy level.

Table 5

POAF predictive models accuracy assessment on test samples for SGB

N	Predictors	Predictor and Its Boundary	Accuracy metrics			
			Sen	Spec	AUC	ACC
1	Age	-	0.5	0.59	0.54	0.57
2	Age, PQ	-	0.58	0.66	0.65	0.64
3	Age, PQ, QRS	-	0.66	0.63	0.71	0.64
4	Age, PQ, QRS, RR	-	0.76	0.76	0.8	0.76
5	Age, PQ, QRS, RR, QT	-	0.77	0.76	0.82	0.76

6	Age, PQ, QRS, RR, QT, RA1*RA2	-	0.72	0.76	0.8	0.75
7	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3	-	0.68	0.78	0.79	0.76
8	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD	-	0.69	0.75	0.78	0.74
9	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD,EF	-	0.68	0.76	0.78	0.75
10	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD,EF,TVI	-	0.68	0.76	0.78	0.75
11	Age	M 55- 74 F 60-78	0.93	0.21	0.57	0.35
12	Age + PQ	170-210 ms	0.25	0.93	0.64	0.8
13	Age, PQ + QRS	50-80 ms	0.72	0.46	0.66	0.5
14	Age, PQ, QRS + RR	1000-1100 ms	0.56	0.75	0.7	0.71
15	Age, PQ, QRS, RR + QT	M>420 ms Ж>440 ms	0.67	0.69	0.72	0.69
16	Age, PQ, QRS, RR, QT + RA1*RA2	> 160 mm^2	0.63	0.74	0.75	0.72
17	Age, PQ, QRS, RR, QT, RA1*RA2 + LA1*LA2	> 150 mm^2	0.69	0.71	0.74	0.71
18	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3 + ESD	>490 mm	0.68	0.71	0.75	0.71

19	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD + EF	45-60%	0.68	0.72	0.75	0.71
20	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF + TVI	-	0.69	0.71	0.75	0.71

For models based on ANN, an accuracy increase was recorded when the predictors range was expanded both in continuous and categorical forms (Table 6). The best ANN model was obtained when all significant predictors were included in categorical form (Sen - 0.74, Spec - 0.73, AUC - 0.75, ACC - 0.73). The latter accuracy is lower than the best model based on SGB, but exceeds the accuracy of the LR model. But alongside, ANN models allow us to confirm the influence significance for the under-consideration predictors.

Table 6
POAF predictive models accuracy assessment on test samples for ANN

N	Predictors	Predictor and Its Boundary	Accuracy metrics			
			Sen	Spec	AUC	ACC
1	Age	-	0.16	0.86	0.56	0.7
2	Age, PQ	-	0.2	0.9	0.59	0.73
3	Age, PQ, QRS	-	0.5	0.77	0.71	0.6
4	Age, PQ, QRS, RR	-	0.6	0.68	0.63	0.64
5	Age, PQ, QRS, RR, QT	-	0.63	0.68	0.68	0.65
6	Age, PQ, QRS, RR, QT, RA1*RA2	-	0.65	0.68	0.71	0.67
7	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3	-	0.68	0.7	0.69	0.69
8	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD	-	0.69	0.72	0.71	0.7
9	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF	-	0.7	0.71	0.71	0.71

10	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF, TVI	-	0.71	0.72	0.72	0.71
11	Age	M 55- 74 F 60-78	0	1.0	0.55	0.81
12	Age + PQ	170-210 ms	0.24	0.94	0.62	0.8
13	Age, PQ + QRS	50-80 ms	0.38	0.8	0.67	0.73
14	Age, PQ, QRS + RR	1000-1100 ms	0.58	0.74	0.71	0.71
15	Age, PQ, QRS, RR + QT	M>420 ms F>440 ms	0.68	0.68	0.72	0.68
16	Age, PQ, QRS, RR, QT + RA1*RA2	> 160 mm^2	0.63	0.75	0.75	0.73
17	Age, PQ, QRS, RR, QT, RA1*RA2 + LA1*LA2	> 150 mm^2	0.65	0.74	0.75	0.72
18	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD	>490 mm	0.65	0.74	0.74	0.73
19	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD + EF	45-60%	0.7	0.71	0.74	0.71
20	Age, PQ, QRS, RR, QT, RA1*RA2, LA2*LA3, ESD, EF + TVI	-	0.74	0.73	0.75	0.73

4. Conclusions

This work presents models for after CABG POAF prediction, developed on the basis of statistical analysis and machine learning methods: intergroup comparison, significant ranges searching, univariate LR, multivariate LR, SGB and ANN. Predictors were received during analysis of 100 pre-operative coronary artery disease patients' characteristics data set. Statistical methods usage made it possible to identify the most significant factors. At the same time, it was possible to put forward hypotheses about the boundaries ranges of that form risk factors. The factors with the highest predictive potential included patients age (55-74 years for men, 60-78 years for women), RR 1000-1100 ms, QRS 50-80 ms, PQ 170-210 ms, QT (> 420 ms for men;> 440 ms - for women), product of linear dimensions of LA> 150 mm^2 and RA> 160 mm^2, presence of TVI, EF 45-60% and LV ESD> 490 mm. These hypotheses were confirmed by univariate, multivariate LR and ANN models. Some of the predictors (EF, TVI, ESD) had nonlinear relationships with the endpoint and did not increase the accuracy of the LR models. The step-by step increase of ANN models quality metrics confirms the influence of these factors on POAF risk. The usage of categorical form indicators didn’t lead to models accuracy degression in all cases considered.

At the same time, the authors best model were obtained with SGB and most significant factors in continuous form. This model for new-onset POAF after CABG prediction according to 4 quality metrics (AUC - 0.82, ACC - 0.76, Sen - 0.77 and Spec - 0.76) is the best compared to previously published ones. Further extension of SGB model predictors reduced the prediction accuracy. Moreover, categorical indicators form usage for SGB also did not improve the models quality, compared to continuous counterparts.

The predictors obtained in our study are explainable by modern pathophysiology concepts of coronary artery disease and AF. So, initially (before surgery), the altered atrial size, impaired LV contractile function and ECG abnormalities are aggravated against the background of operational stress, appear to be a substrate that contributes to the pathological arrhythmia’s occurrence. Complexity of the clinical interpretation for SGB and ANN is indisputable fact, but as shown in our experiment some predictors used for modeling could be widespread markers of patient’s functional status and their predictive value already has been shown in a number of works [21]. However, previously not used predictors, such as ESD, TVI and RA size, were identified, which is the task of further research.

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