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HYBRID INTELLIGENT SYSTEM FOR STRATIFYING THE RISK OF CORONARY HEART DISEASE

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Abstract. The article proposes a hybrid intelligent system for stratifying the risk of coronary heart disease (CHD). It includes ensemble forecasting, natural language processing, and explainable AI technologies. It is demonstrated that the integration of structured clinical features and unstructured text data improves the accuracy of CHD risk assessment compared to the traditional SCORE2 scales. On test datasets, high values of AUC-ROC and F1-score were achieved, while the interpretability of the predictions is ensured by constructing waterfall plots that reflect the contribution of key risk factors. The developed software package will be useful in cardiology for supporting clinical decision-making.

Keywords: hybrid intelligent system, ensemble machine learning, cardiovascular outcome prediction, natural language processing, artificial intelligence, SHAP analysis, clinical decision support

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ГИБРИДНАЯ ИНТЕЛЛЕКТУАЛЬНАЯ СИСТЕМА СТРАТИФИКАЦИИ РИСКА ИШЕМИЧЕСКОЙ БОЛЕЗНИ СЕРДЦА

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Аннотация. В статье предложена гибридная интеллектуальная система для стратификации риска ишемической болезни сердца (ИБС), которая объединяет ансамблевое прогнозирование, обработку естественного языка и технологии объяснимого ИИ. Показано, что интеграция структурированных клинических признаков и неструктурированных текстовых данных повышает точность оценки риска ИБС по сравнению с традиционными шкалами SCORE2. На тестовых выборках достигнуты высокие значения метрик качества AUC-ROC и F1-score, при этом интерпретируемость прогнозов обеспечивается построением диаграмм типа «водопад» (waterfall plots), отражающих вклад ключевых факторов риска. Разработанный программный комплекс найдет применение в кардиологии для поддержки принятия врачебных решений.

Ключевые слова: гибридная интеллектуальная система, ансамблевое машинное обучение, прогнозирование сердечно-сосудистых исходов, обработка естественного языка, искусственный интеллект, SHAP-анализ, поддержка принятия врачебных решений

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Introduction

There is a growing clinical need for tools that enable physicians to rapidly and reliably assess the risk of adverse outcomes in patients with coronary heart disease (CHD). The effectiveness of such tools depends directly on the completeness and relevance of the data used. Contemporary electronic health record systems provide access to a wide range of information – from structured measurements to narrative clinical notes – creating new opportunities for more advanced prognostic models.

The object of the study in this paper is the clinical data from patients with CHD: anthropometric and laboratory parameters, electrocardiographic measurements, as well as electronic medical records. Based on these data, a hybrid intelligent risk stratification system is developed, that is intended for practical application in routine clinical practice.

Current approaches to risk stratification for CHD have evolved along several parallel lines. Each makes a significant contribution in prediction, yet none fully resolves the problem.

A substantial body of research relies on structured clinical and laboratory data in combination with traditional statistical models or ensemble machine-learning (ML) methods. Classical risk stratification scores widely used due to their simplicity and transparency; however, their predictive capability is limited in heterogeneous patient populations. ML methods can improve prediction accuracy compared to linear models and clinical risk scores, especially when accounting for nonlinear interactions among predictors. At the same time, such models often behave as “black boxes”, which impedes their adoption in clinical practice, where the physicians must understand the rationale behind a prediction.

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A separate line of research addresses automated analysis of instrumental data, in particular electrocardiograms (ECGs). The use of convolutional neural networks and deep-learning methods for ECG signal processing demonstrates high sensitivity to early signs of ischemia, including cases in which visual interpretation is challenging [1].

An important source of clinically relevant information is the unstructured text in electronic medical records (EMRs). Recent years have seen rapid development of natural language processing (NLP) methods for entity extraction, term normalization, and identification of key features in physician notes. The use of libraries such as spaCy, as well as transformer models (BERT, BioBERT), makes it possible to extract symptoms, diagnoses, risk factors, and trajectories of patient status from texts with acceptable accuracy [2, 3]. Nevertheless, most NLP-solutions in cardiology target classification or information retrieval tasks rather than direct integration into decision-support systems for risk stratification.

NLP methods enable automatic encoding of symptom dynamics, qualitative descriptions of the patient's status, and mentions of comorbidities and therapy.

In [4–7], NLP pipelines based on rules, dictionaries of medical terms (including adapted Russian-language resources), and neural architectures (BERT-like models for Russian) are described[1]. It has been shown that adding NLP-derived features to structured data improves the predictive performance, with an increase in AUC-ROC of 0.02–0.05 depending on the task and dataset. This supports the hypothesis that unstructured data carry additional prognostic value.

Since the early 2010s, ML models have been increasingly applied in cardiology, demonstrating higher predictive accuracy compared to traditional risk scores. In some cases, ML models outperform SCORE scales by 10–30 % in AUC-ROC, supporting a transition toward more flexible algorithms.

In [8, 9], the implementation of ML solutions in clinical practice is addressed: integration with medical information systems (MISs) for automatic risk calculation during patient registration; development of physician-facing interfaces in which the prediction is accompanied by an explanation; pilot projects in inpatient and outpatient settings, where the system helps prioritize patients for further examination.

To address the "black box" problem, in [10], explainable AI methods are actively employed: SHAP (SHapley Additive exPlanations), which quantifies the contribution of each feature to a prediction and enables comparison of factor effects across patients; LIME, which provides local explanations for individual predictions; and waterfall plots, that visualize which factors increase or decrease risk. In cardiological studies, SHAP analysis is used to interpret models predicting major adverse cardiac events (MACE), mortality, and the risk of hospitalization. It helps identify unexpected patterns and align model conclusions with clinical insight.

Another promising direction is ensemble methods, which are widely used in medical prediction. In [11–15], architectures in which individual models are trained on different subsets of features are described; the final prediction obtained through weighted voting or stacking; different types of data are processed by specialized modules whose outputs are then combined. Such hybrid systems demonstrate more stable results on independent datasets and generalize better across data from different institutions. At the same time, ensuring clinical interpretability remains a key challenge: physicians must understand why the system produced a given prediction. Several publications describe architectures that combine structured data with imaging results or signals from wearable devices [16–20]. Moreover, there is growing interest in hybrid models in which ML algorithms are complemented by rule-based, ontology-based, or fuzzy-logic components, improving robustness of predictions and partially addressing interpretability [21–24]. Despite these advances, the literature contains virtually no studies in which such a hybrid architecture has been implemented as a unified decision-support

[1] Cardiovascular diseases (CVDs), Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds) (Accessed 13.10.2026)

tool for CHD risk stratification that simultaneous processes structured data, narrative records, and instrumental measurements, while providing explanations intelligible to clinicians.

Despite active development of intelligent clinical decision-support systems in cardiology, their widespread adoption in clinical practice is still hindered by a number of significant barriers. Key limitations include the need for external validation on independent patient cohorts, concerns about data quality and representativeness, and strict regulatory requirements for medical software. These factors directly affect clinician trust in algorithms and determine the feasibility of integrating such solutions into existing MISs.

The aim of this study is to present a hybrid intelligent system for risk stratification in CHD and to demonstrate its effectiveness and practical applicability in a clinical setting. To achieve this goal, the study implements an architecture that combines an ensemble of ML models with a NLP module, and also carries out a set of validation procedures aimed at assessing the stability of predictions and ensuring reproducibility of results.

Methods

A comprehensive approach was employed in developing a hybrid intelligent system for risk stratification in CHD, combining statistical analysis, ML methods, model interpretation techniques, and the software implementation of an analytical pipeline.

In this study, a publicly available dataset (heart.csv) was used, containing patient records, clinical features, and a binary outcome indicating CHD status. During the data preprocessing stage, the following procedures were carried out:

- imputation of missing values;
- encoding of categorical variables;
- standardization of numerical features to a common scale.

Because the outcome was imbalanced, we applied class-balancing procedures to reduce the model's bias toward the majority class.

For the initial examination of the data structure, descriptive statistical analysis was used, including the calculation of key characteristics and visualization of feature distributions. Correlation analysis was applied to identify strong associations between predictors and the outcome, as well as to detect multicollinearity. Cluster analysis was employed at certain stages to test whether natural subgroups of patients with similar clinical profiles exist – a question relevant to the choice of a stratified modelling approach.

Since the task of risk stratification requires high accuracy and robustness to data variability, an ensemble method was developed that combines several algorithms with different inductive biases: gradient boosting as the primary predictor; logistic regression to obtain interpretable coefficients and to verify the linearity of relationships; random forest to assess feature importance and to ensure robustness to outliers. The final prediction was generated through weighted voting, with weights determined based on their performance in cross-validation. This approach allowed us to account for both quantitative patterns and qualitative features of clinical scenarios typical of different patient subgroups.

To objectively assess the quality of the models and to mitigate overfitting, the data were split into training (80 %) and test (20 %) sets while maintaining the class distribution. The performance was evaluated using metrics adapted for imbalanced data. To obtain a more reliable assessment of the results stability, cross-validation with repeated runs was used.

A key component of the hybrid system is the clinical interpretability of the predictions. To achieve this, SHAP analysis was used, which allows obtaining both a global assessment of feature importance and local explanations for individual predictions. This ensures that model conclusions align with clinical understanding and helps identify unexpected patterns that may warrant further investigation.

The study was developed in Python using the following libraries:

- Pandas and NumPy – for data processing and transformation;
- Scikit-Learn – for basic ML methods, cross-validation, and metrics;
- Imbalanced-Learn – for class imbalance handling;
- XGBoost – for building gradient boosting models;
- SHAP – for model interpretation;
- spaCy – for preprocessing text fields;
- Matplotlib and Seaborn – for result visualization;
- Streamlit and FastAPI – for developing the user interface and API of the hybrid system.

Thus, the proposed methodological framework ensures not only high accuracy in predicting the risk of CHD but also transparency of the decisions made by the system, which is crucial for the implementation of such tools in clinical practice.

Results and discussion

Methods of analysis and the procedure for calculating indicators

The study uses the open dataset heart.csv, which is widely used in research on CHD prediction [16]. The dataset contains 918 records, 11 initial clinical features, and a binary target variable indicating the presence of CHD. The class distribution is as follows: 508 patients (55.3 %) with CHD and 410 patients (44.7 %) without CHD (moderate class imbalance).

Feature description:

- Numerical: age (Age), resting blood pressure (RestingBP), cholesterol (Cholesterol), maximum heart rate (MaxHR), ST-segment depression (Oldpeak).
- Categorical: sex (Sex), chest pain type (ChestPainType), fasting blood sugar level (FastingBS), resting ECG results (RestingECG), presence of exercise-induced angina (ExerciseAngina), ST-segment slope (ST_Slope).

Artifactual zeros in the restingBP and cholesterol fields (which cannot be clinically equal to 0) were replaced with NaN and subsequently imputed using median values calculated from non-zero observations.

Stratified splitting into a training set (80 %) and a test set (20 %) was performed while preserving the class proportions.

To improve the model's predictive performance and capture clinically relevant interactions, eight features were developed:

- Age_Chol_Interaction = age × cholesterol;
- Age_BP_Interaction = age × resting blood pressure;
- Age_squared;
- BP_Category;
- Cholesterol_Category;
- HR_Angina_Interaction;
- Slope_Oldpeak_Interaction;
- Pain_Sex.

All the features were included in the final set along with the original eleven parameters. To automatically extract eleven clinical parameters from unstructured Russian text, an NER model was developed based on the spaCy library (version 3.7.2). Since there were no annotated clinical texts in Russian, a synthetic corpus was created by generating a variable text for each of the 918 dataset records; the text contains randomly selected marker phrases for each feature and a random order of their mention.

The spaCy ru_core_news_sm model was used as the initial base, to which an NER component with 11 labels (feature names) was added. The model was trained for 20 epochs with a batch size of 8 and a dropout rate of 0.35. The optimizer used was adam (with the default learning rate in spaCy).

The extracted values are checked for compliance with clinical ranges and normalized: “yes” → 1, “no” → 0 for binary features; “male” → M, “female” → F; textual variants of diagnoses are converted to the standard values used in the model (e.g., ASY, ATA, NAP, TA).

Three algorithms were evaluated:

- Logistic Regression with L2 regularization (parameter C = 0.1, solver: liblinear);
- Random Forest with 150 trees;
- XGBoost with hyperparameters tuned using GridSearchCV (n_estimators = 100, max_depth = = 3, learning_rate = 0.1).

A pipeline was used for all models: Preprocessing (standardization of numerical features, one-hot encoding of categorical features); SMOTE for class balancing in the training set; model.

A VotingClassifier with soft voting was built. The model weights were selected empirically: XGBoost – 0.5, Random Forest – 0.25, Logistic Regression – 0.25.

Stratified five-fold cross-validation was applied to the training set (X_train, y_train) to tune hyperparameters and assess stability. Final testing was performed on the held-out test set (X_test, y_test). Metrics included AUC-ROC, Recall (sensitivity), Precision, F1 score, and Calibration (calibration curve). The SHAP method was used to explain the predictions [17]. The analysis was carried out for XGBoost as the most influential component of the ensemble. Global feature importance was estimated using the mean absolute SHAP values. Local interpretation was implemented as waterfall plots showing the contribution of each feature to the prediction for a specific patient.

All developed modules were integrated into a web application built with the streamlit framework (version 1.2+). The application includes three tabs:

1. *Prediction and Interpretation*: for manual input of 11 parameters via sliders and drop-down lists, and for displaying the prediction;
2. *Text Analysis*: for entering unstructured text in Russian, a button to launch the NLP module, and displaying the extracted values with visual confirmation (checkmarks) in the sidebar;
3. *Methodology*: a description of model, metrics, and interpretation.

The application is implemented using a modular structure (Files: app.py, utils.py, config.py), which ensures scalability and ease of maintenance.

System output characteristics and analysis of predictive accuracy

The results on the held-out test set are presented in Table 1. The ensemble outperforms each of the base models across all metrics, achieving AUC-ROC of 0.938, Recall of 0.912, and Precision of 0.930.

Table 1

Quality metrics on the test set

Model	AUC ROC	Recall	Precision	F1 score
Logistic Regression	0.889	0.833	0.882	0.857
Random Forest	0.908	0.863	0.902	0.882
XGBoost	0.931	0.892	0.917	0.904
Ensemble (Voting)	**0.938**	**0.912**	**0.930**	**0.921**

Stratified five-fold cross-validation on the training set demonstrated the stability of the results: mean AUC-ROC = 0.932 ± 0.030, mean Recall = 0.882 ± 0.040, mean Precision = 0.901 ± 0.035. The calibration curve (Fig. 1) shows a good agreement between the predicted probabilities and the actual frequencies, which confirms the reliability of the model’s probabilistic estimates.

On the test set (20 % of the 938 generated examples), the following metrics were achieved: Precision = 0.73, Recall = 0.71, F1 score = 0.72.

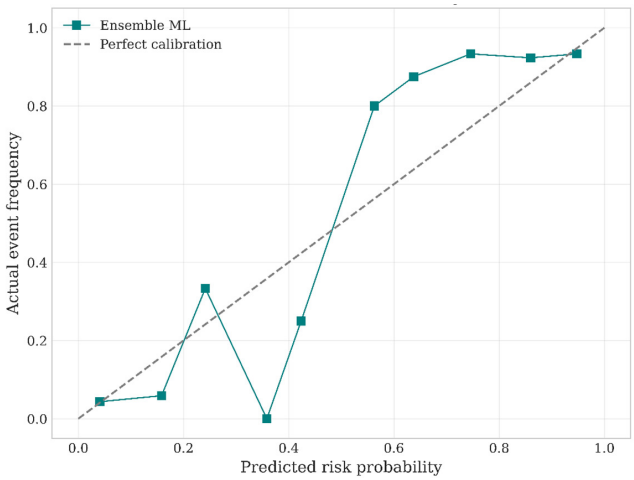


Fig. 1. Calibration curve

The best performance was observed for the Age, Sex, and FastingBS (F1 > 0.80) features (Table 2). The features RestingECG and ST_Slope proved to be the most challenging to extract, which is due to their lower frequency of mention in the generated texts.

Table 2

Detailed metrics of the NLP module by entity type

Feature	Precision	Recall	F1 score
Age	0.89	0.92	0.90
Sex	0.91	0.88	0.89
ChestPainType	0.78	0.75	0.76
RestingBP	0.79	0.72	0.75
Cholesterol	0.82	0.76	0.79
FastingBS	0.84	0.86	0.85
RestingECG	0.64	0.60	0.62
MaxHR	0.77	0.73	0.75
ExerciseAngina	0.72	0.70	0.71
Oldpeak	0.70	0.66	0.68
ST_Slope	0.59	0.56	0.57

Global feature importance analysis (Fig. 2) showed that the greatest impact on the prediction is exerted by: ST_Slope (Slope UP), Pain_Sex_Interaction_M_ASY, ChestPainType_ASY.

To illustrate the local interpretation, Fig. 3 shows a waterfall plot for a patient at high risk (probability of CHD 0.87). The plot reveals that the main factors increasing the risk were ST_Slope = UP (0.84), Age_BP_Interaction (0.21), and FastingBS_0 (0.18). The greatest risk-reducing effect was provided by ChestPainType_ASY (–0.56), Pain_Sex_Interaction_M_ASY (–0.5).

The developed application allows you to:

- Enter data manually and get a prediction and a SHAP plot in real time;
- Upload a clinical report text, automatically extract the parameters, and use them for prediction;
- Save the results as a report (the functionality is being expanded).

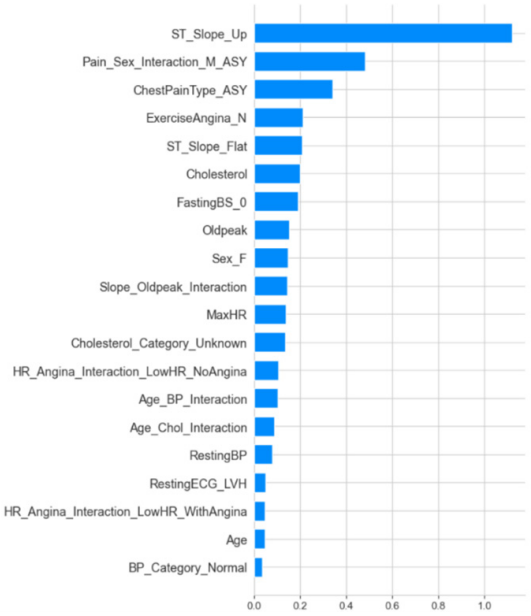


Fig. 2. Histogram of the mean absolute SHAP importance (overall predictive power of the features)

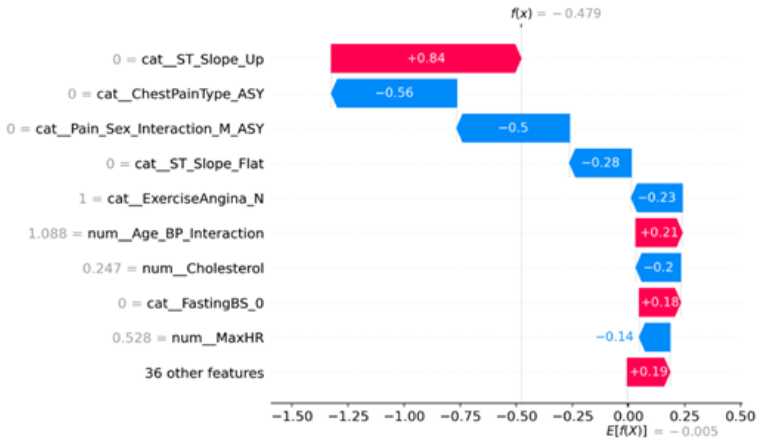


Fig. 3. Personalized analysis of factors (SHAP-waterfall)

Testing the application on 50 anonymized clinical cases confirmed the correct integration of all modules and a response time of less than 3 seconds per calculation (including SHAP).

Analysis of the obtained data and assessment of practical significance

The proposed system outperforms the traditional SCORE/SCORE2 scales in terms of accuracy (AUC ROC 0.938 vs 0.75–0.80). The high Recall (0.912) is of critical clinical importance – it reduces the likelihood of missing patients with CHD.

Compared to other studies on the use of ML for CHD prediction, the system is distinguished by the integration of NLP for automatic data input and a built-in mechanism for explaining predictions. This helps overcome the “black box” barrier and increases physician trust in the system.

Automatic data extraction from text can reduce the time a physician spends filling out forms by up to 50 % (according to the data provided in the technical specification). This is achieved through the use of an NLP module that successfully recognizes 11 parameters with an F1-score of 0.72 – an acceptable level for decision support (the target of F1 ≥ 0.70 has been achieved).

Interpretability via SHAP allows the physician to understand which factors had the greatest impact on the prediction and to justify the need for additional examinations or therapy adjustments.

1. Data: A single dataset was used, which does not reflect the full diversity of real clinical data. External validation on independent samples from different medical centers is required.

2. NLP module: trained on synthetic data, which may lead to a decrease in performance when processing texts containing specific abbreviations, spelling errors, and complex syntactic structures.

3. Model: the use of SMOTE for class balancing may lead to the generation of unrealistic examples in small datasets; in the future, other methods (e.g., class weighting) could be employed.

4. Hardware dependency: the application is designed to run on a server with 2+ vCPU and 4 GB of RAM; in case of low performance, the response time may exceed 3 seconds.

Conclusion

In this work, a hybrid intelligent system for stratifying the risk of CHD has been developed and validated, including:

- an ensemble of ML models with an AUC-ROC of 0.938 and a Recall of 0.912, which significantly outperforms existing clinical scales;
- an NLP processing module based on spaCy, which enables the extraction of 11 clinical parameters from Russian text with an F1-score of 0.72;
- an explainable AI module based on SHAP, which visualizes the contribution of factors to the individual prediction.

All components are integrated into a Streamlit-based web application, which can be used in clinical practice as a decision-support tool for physicians. The system is ready for further clinical trials and potential integration into electronic health records.

REFERENCES

1. **Zhang P.-I., Hsu C.-C., Kao Y. et al.** Real-time AI prediction for major adverse cardiac events in emergency department patients with chest pain. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*, 2020, Vol. 28, Article no. 93. DOI: 10.1186/s13049-020-00786-x

2. **Olsson de Capretz P., Björkelund A., Björk J., Ohlsson M., Mokhtari A., Nyström A., Ekelund U.** Machine learning for early prediction of acute myocardial infarction or death in acute chest pain patients using electrocardiogram and blood tests at presentation. *BMC Medical Informatics and Decision Making*, 2023, Vol. 23, Article no. 25. DOI: 10.1186/s12911-023-02119-1

3. **Liu N., Koh Z.X., Goh J., Lin Z., Haaland B., Ting B.P., Ong M.E.H.** Prediction of adverse cardiac events in emergency department patients with chest pain using machine learning for variable selection. *BMC Medical Informatics and Decision Making*, 2014, Vol. 14, Article no. 75. DOI: 10.1186/1472-6947-14-75

4. **Tolpygina S.N., Martsevich S.Yu.** Study of a trend in the frequency of using main drug classes indicated for the treatment of patients with chronic coronary heart disease in 2004 to 2014: data from the CHD prognosis registry. *The Clinician*, 2016, Vol. 10, No. 1, Pp. 29–35. DOI: 10.17650/1818-8338-2016-10-1-29-35

5. **Tolpygina S.N., Martsevich S.Yu.** Cardiovascular risk stratification in stable coronary artery disease based on prognostic scores and models. *Cardiovascular Therapy and Prevention*, 2020, Vol. 19, No. 3, Pp. 240–247. DOI: 10.15829/1728-8800-2020-2528

6. **Tolpygina S.N., Martsevich S.Yu., Deev A.D.** Enhanced risk stratification scale for predicting death and non-fatal cardiovascular events in patients of the PROGNOZ IBS registry. *Cardiovascular Therapy and Prevention*, 2021, Vol. 20, No. 7, Pp. 143–152. DOI: 10.15829/1728-8800-2021-3060

7. **Tolpygina S.N., Martsevich S.Yu., Gofman E.A., Deev A.D.** Prognostic value of intstrumental diagnostics in chronic coronary heart disease. Data from "PROGNOS CHD". *Cardiovascular Therapy and Prevention*, 2014, Vol. 13, No. 4, Pp. 29–35. DOI: 10.15829/1728-8800-2014-4-29-35

8. **Golukhova E.Z., Keren M.A., Zavalikhina T.V., Bulaeva N.I., Akatov D.S., Sigaev I.Yu., Yakhyaeva K.B., Kolesnikov D.A.** Potential of machine learning methods in operational risk stratification in patients with coronary artery disease scheduled for coronary bypass surgery. *Russian Journal of Cardiology*, 2023, ol. 28, No. 2, Article no. 5211. DOI: 10.15829/1560-4071-2023-5211

9. **Motwani M., Dey D., Berman D.S., et al.** Machine learning for prediction of all-cause mortality in patients with suspected coronary artery disease: a 5-year multicentre prospective registry analysis. *European Heart Journal*, 2017, Vol. 38, No. 7, Pp. 500–507. DOI: 10.1093/eurheartj/ehw188

10. **Kakadiaris I.A., Vrigkas M., Yen A.A., Kuznetsova T., Budoff M., Naghavi M.** Machine Learning Outperforms ACC/AHA CVD Risk Calculator in MESA. *Journal of the American Heart Association*, 2018, Vol. 7, No. 22, Article no. e009476. DOI: 10.1161/JAHA.118.009476

11. **Commandeur F., Slomka P.J., Goeller M., et al.** Machine learning to predict the long-term risk of myocardial infarction and cardiac death based on clinical risk, coronary calcium, and epicardial adipose tissue: a prospective study. *Cardiovascular Research*, 2020, Vol. 116, No. 14, P. 2216–2225. DOI: 10.1093/cvr/cvz321

12. **Piepoli M.F., Hoes A.W., Agewall S., et al.** 2016 European Guidelines on cardiovascular disease prevention in clinical practice: The Sixth Joint Task Force of the European Society of Cardiology and Other Societies on Cardiovascular Disease Prevention in Clinical Practice (constituted by representatives of 10 societies and by invited experts). Developed with the special contribution of the European Association for Cardiovascular Prevention & Rehabilitation (EACPR). *European Heart Journal*, 2016, Vol. 37, No. 29, P. 2315–2381. DOI: 10.1093/eurheartj/ehw106

13. **Conroy R.M., Pyörälä K., Fitzgerald A.P., et al.** Estimation of ten-year risk of fatal cardiovascular disease in Europe: the SCORE project. *European Heart Journal*, 2003, Vol. 24, No. 11, P. 987–1003. DOI: 10.1016/s0195-668x(03)00114-3

14. **SCORE2 working group and ESC Cardiovascular risk collaboration.** SCORE2 risk prediction algorithms: new models to estimate 10-year risk of cardiovascular disease in Europe. *European Heart Journal*, 2021, Vol. 42, No. 25, Pp. 2439–2454. DOI: 10.1093/eurheartj/ehab309

15. **Visseren F.L.J., Mach F., Smulders Y.M., et al.** 2021 ESC Guidelines on cardiovascular disease prevention in clinical practice. *European Heart Journal*, 2021, Vol. 42, No. 34, Pp. 3227–3337. DOI: 10.1093/eurheartj/ehab484

16. **VanHouten J.P., Starmer J.M., Lorenzi N.M., Maron D.J., Lasko T.A.** Machine learning for risk prediction of acute coronary syndrome. *AMIA Annual Symposium Proceedings Archive*, 2014, 2014, Pp. 1940–1949.

17. **Topol E.J.** High performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 2019, Vol. 25, P. 44–56. DOI: 10.1038/s41591-018-0300-7

18. **Krittanawong C., Zhang H., Wang Z., Aydar M., Kitai T.** Artificial intelligence in precision cardiovascular medicine. *Journal of the American College of Cardiology* (*JACC*), 2017, Vol. 69, No. 21, Pp. 2657–2664. DOI: 10.1016/j.jacc.2017.03.571

19. **Johnson K.W., Torres Soto J., Glicksberg B.S., Shameer K., Miotto R., Ali M., Ashley E., Dudley J.T.** Artificial intelligence in cardiology. *Journal of the American College of Cardiology* (*JACC*), 2018, Vol. 71, No. 23, Pp. 2668–2679. DOI: 10.1016/j.jacc.2018.03.521

20. **Lundberg S.M., Lee S.-I.** A unified approach to interpreting model predictions. *arXiv:1705.07874*, 2017. DOI: 10.48550/arXiv.1705.07874

21. **Al'Aref S.J., Anchouche K., Singh G., et al.** Clinical applications of machine learning in cardiovascular disease and its relevance to cardiac imaging. *European Heart Journal*, 2019, Vol. 40, No. 24, Pp. 1975–1986. DOI: 10.1093/eurheartj/ehy404

22. **Dey D., Slomka P.J., Leeson P., Comaniciu D., Shrestha S., Sengupta P.P., Marwick T.H.** Artificial intelligence in cardiovascular imaging: JACC state-of-the-art review. *Journal of the American College of Cardiology* (*JACC*), 2019, Vol. 73, No. 11, Pp. 1317–1335. DOI: 10.1016/j.jacc.2018.12.054

23. **Janosi A., Steinbrunn W., Pfisterer M., Detrano R.** Heart Disease. *UCI Machine Learning Repository*, 1989. DOI: 10.24432/C52P4X

24. **Lundberg S.M., Erion G., Chen H., DeGrave A., Prutkin J.M., Nair B., Katz R., Himmelfarb J., Bansal N., Lee S.-I.** From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence*, 2020, Vol. 2, Pp. 56–67. DOI: 10.1038/s42256-019-0138-9

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