Reviews in Cardiovascular Medicine

Rev. Cardiovasc. Med. **2026**; 27(11): 54303
https://doi.org/10.31083/RCM54303

Review

Artificial Intelligence in Cardiovascular Disease: Current Applications, Methodological Challenges, and Clinical Translation

Basheer Abdullah Marzoog[1,*], Daria Gognieva[1], Peter Chomakhidze[1], Philipp Kopylov[1]

[1]Institute of Personalized Cardiology of The Center "Digital Biodesign and Personalized Healthcare" of Biomedical Science and Technology Park, Federal State Autonomous Educational Institution of Higher Education I.M. Sechenov First Moscow State Medical University of the Ministry of Health of the Russian Federation (Sechenovskiy University), 119991 Moscow, Russia

*Correspondence: marzug_b_a@staff.sechenov.ru (Basheer Abdullah Marzoog)

Academic Editor: Sherry Ann Brown

Submitted: 27 May 2026 Revised: 27 August 2026 Accepted: 3 September 2026 Published: 10 November 2026

Abstract

Artificial intelligence (AI), including machine learning (ML) and deep learning (DL), is increasingly being investigated for cardiovascular diagnosis, risk stratification, and prognostic assessment, leveraging electrocardiography, cardiovascular imaging, electronic health records, wearable devices, and molecular data. This review summarizes current AI applications in ischemic heart disease, acute coronary syndromes, heart failure, arrhythmias, and structural cardiovascular disease, and critically examines the methodological requirements for clinical translation. Particular attention is given to model taxonomy, data leakage, overfitting, external validation, calibration, dataset shift, explainability, clinical utility, privacy, cybersecurity, and regulatory considerations. Current evidence shows that AI can identify clinically relevant patterns and may complement conventional cardiovascular assessment; however, high performance in retrospective or selected datasets does not necessarily translate into improved patient outcomes. Therefore, robust patient-level data separation, independent external and prospective validation, calibration assessment, workflow evaluation, and post-deployment monitoring are essential. Emerging multimodal, hybrid, and foundation-model approaches may further improve cardiovascular prediction, but their clinical value requires rigorous evaluation. Currently, AI should primarily be regarded as a complementary decision-support tool rather than a replacement for established diagnostic or prognostic standards.

Keywords: artificial intelligence; heart disease; ischemic heart disease; heart failure; acute coronary syndrome; breathome; lipidome; volatilome; machine learning model

1. Introduction

The cardiac pathology remains a global issue despite the current achievements in the medical field [1]. The 2024 Heart Disease and Stroke Statistics report highlights the substantial global prevalence and burden of cardiovascular disease [1]. For example, heart failure remains a critical condition with ongoing challenges, despite advancements in treatment. A review published in 2025 summarized advances in heart failure research and management during 2024 [2]. Recent discussions in global cardiology emphasize the necessity for continuous education and research to address cardiac pathology as a major public health issue.

The integration of artificial intelligence into cardiology offers opportunities to improve diagnosis, treatment, and cardiovascular risk stratification [3,4,5]. In general, artificial intelligence refers to computational systems, including machine-learning algorithms and neural networks, that can perform tasks such as pattern recognition, prediction, and decision support with limited human intervention [6].

Machine learning (ML) models can potentially surpass human performance in certain tasks, such as detecting subtle abnormalities in cardiac images that may be missed by visual inspection. This can lead to earlier and more accurate diagnoses, enabling timely interventions [7]. ML can automate time-consuming tasks, such as image segmentation and measurement, freeing up clinicians to focus on more complex aspects of patient care. This can improve workflow efficiency and reduce healthcare costs. ML approaches can integrate clinical, demographic, imaging, biomarker, and other patient-level data to support individualized cardiovascular risk prediction and clinical decision-making [3,8,9]. ML models can predict the likelihood of future cardiac events, such as heart attacks or hospitalizations, allowing for proactive interventions and improved patient outcomes.

ML showed the feasibility to detect atrial fibrillation from smartwatch data, predict obstructive coronary artery disease from coronary CT angiography, and to detect hypertrophic cardiomyopathy from electrocardiograms (ECGs) [10,11,12].

Unlike reviews that primarily catalogue individual applications or report model-performance estimates, the present review examines cardiovascular artificial intelligence (AI) from both clinical and methodological perspectives. Particular emphasis is placed on the factors that determine whether promising retrospective performance can translate into meaningful clinical benefit, including

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data leakage, external validation, calibration, clinical utility, dataset shift, explainability, governance, and post-deployment monitoring. We further organize emerging approaches according to methodological class and clinical tasks to highlight the gap between algorithm development and routine cardiovascular implementation.

2. Review Methodology

This study was conducted as a narrative review of artificial intelligence and machine-learning applications in cardiovascular medicine. Relevant literature was identified through AI-assisted searches using Consensus AI, Scopus AI, and Perplexity AI. Search terms included combinations of "artificial intelligence", "machine learning", "deep learning", "cardiovascular disease", "coronary artery disease", "acute coronary syndrome", "heart failure", "arrhythmia", "electrocardiography", "cardiac imaging", "risk prediction", and "prognosis". Priority was given to original clinical investigations, external-validation studies, systematic reviews, meta-analyses, major scientific statements, and methodological publications relevant to clinical implementation. The literature was synthesized narratively according to AI methodology, cardiovascular condition, clinical application, validation strategy, diagnostic or prognostic performance, and barriers to clinical implementation. As this was a narrative rather than a systematic review, a formal systematic screening protocol, quantitative study-selection flow diagram, and standardized risk-of-bias assessment were not undertaken. Consequently, the review should be interpreted as a critical narrative synthesis rather than an exhaustive systematic evaluation of the available evidence.

3. Methodological Taxonomy of Artificial Intelligence Models

Cardiovascular AI encompasses several related but methodologically distinct approaches. Conventional supervised machine-learning methods include logistic-regression-based learning, decision trees, random forests, support-vector machines, gradient boosting, and related algorithms trained using predefined clinical or engineered features. Deep-learning approaches, including convolutional neural networks, recurrent neural networks, long short-term memory networks, and transformer-based architectures, can learn hierarchical representations directly from ECG signals, images, or longitudinal data. Unsupervised and self-supervised methods can identify latent patient phenotypes or learn representations without conventional outcome labels. Hybrid and ensemble approaches combine multiple algorithms, clinical scores, or data modalities to improve robustness or capture complementary information [13]. More recently, multimodal and foundation-model approaches have sought to integrate ECG, imaging, electronic health records, biomarkers, wearable signals, and other clinical information within unified predictive frameworks. These methodological distinctions are clinically relevant because model complexity, interpretability, data requirements, susceptibility to overfitting, and validation requirements differ considerably among approaches.

4. Clinical Applications of Artificial Intelligence in Cardiovascular Disease

Cardiovascular diseases remain a leading cause of morbidity and mortality worldwide. They encompass a broad range of conditions, including ischemic heart disease, acute coronary syndromes, heart failure, arterial hypertension, valvular and congenital heart disease, and cardiac arrhythmias [8,14,15,16]. Improving early detection, risk stratification, and clinical decision-making may contribute to better cardiovascular outcomes. Artificial intelligence and machine-learning approaches are increasingly being investigated as complementary tools to support these objectives [17,18,19,20,21].

4.1 Ischemic Heart Disease and Acute Coronary Syndromes

Artificial intelligence has been increasingly investigated for the diagnosis and risk stratification of ischemic heart disease and coronary artery disease. Machine-learning methods have also been developed to estimate fractional flow reserve (FFR) noninvasively from coronary computed tomography angiography, enabling assessment of the functional significance of coronary artery stenoses [7,22]. Applications include stress electrocardiography, stress echocardiography, 12-lead ECG analysis, coronary imaging, and exhaled-breath analysis. In one study, a machine-learning model based on exhaled-breath biomarkers achieved an area under the receiver operating characteristic curve (AUROC) of 0.838 for identifying ischemic heart disease [23]. Artificial intelligence has also been applied to electrocardiography, echocardiography, cardiovascular imaging, exhaled-breath analysis, robotic-assisted percutaneous coronary intervention, and automated assessment of coronary stenosis during diagnostic coronary angiography [23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,40,41,42,43,44,45,46].

Machine learning applications in cardiac stress testing, particularly in stress electrocardiograms (ECGs) and stress echocardiography, show promise in improving diagnostic accuracy for coronary artery disease (CAD). ML models have demonstrated high sensitivity and specificity rates, with some achieving above 96% and 92.7%, respectively, in stress ECGs and stress echocardiography. These advances may support more accurate assessment of coronary artery disease during cardiac stress testing [44]. Furthermore, machine-learning-based clinical decision support has shown promise in improving the selection of patients referred for invasive coronary angiography, potentially re-

ducing unnecessary procedures. However, this benefit requires confirmation through prospective clinical evaluation [47].

Machine-learning models have also been applied to standard 12-lead ECGs to detect acute coronary occlusion myocardial infarction. In an international evaluation, an AI-based ECG model achieved a diagnostic accuracy of 90.9% (95% CI: 89.7%–92.0%) for identifying occlusion myocardial infarction [48]. These findings illustrate the potential of AI-assisted ECG analysis in evaluating patients with suspected acute coronary syndromes.

4.2 Arrhythmias and Electrophysiology

Artificial intelligence has also been applied to ECG-based detection and prediction of cardiac arrhythmias, with several studies reporting high diagnostic performance [49]. ECG signal quality remains an important limitation because poor-quality recordings may reduce model reliability and generalizability. Broader and more representative datasets are therefore needed to minimize bias and improve performance across different clinical populations [26,47,50,51,52,53,54].

A single-center study used machine learning to identify cardiac pathologies from Holter recordings. The investigators analyzed heart-rate variability time series and related markers using a neural network to classify participants as healthy or as having atrial fibrillation, congestive heart failure, or other cardiac conditions. The study also applied network analysis to RR-interval series and identified different topological patterns across diagnostic groups. The neural-network model achieved up to approximately 85% successful classifications in distinguishing healthy patients from those with atrial fibrillation or congestive heart failure [55].

4.3 Heart Failure

Machine-learning and deep-learning approaches have also been evaluated for heart-failure detection and prognostic assessment. Kwon et al. [16] developed and externally validated a deep-learning ECG model for identifying heart failure with reduced ejection fraction, while Attia et al. [25] prospectively evaluated smartwatch-enabled detection of left ventricular systolic dysfunction. More recently, Zhang et al. [13] developed a hybrid survival model for mortality prediction in patients with advanced heart failure and renal dysfunction, including independent external validation. These studies illustrate the potential of AI not only for diagnosis but also for risk stratification and longitudinal assessment in heart failure.

4.4 Structural and Valvular Heart Disease

Artificial intelligence has also been explored in structural and valvular heart disease. Deep-learning approaches have been applied to ECG-based detection of left-sided valvular heart disease and aortic stenosis [38,41], while AI-assisted echocardiography has been investigated for automated cardiac assessment and detection of clinically relevant structural abnormalities [32,35]. These applications suggest a potential role for AI in supporting earlier recognition and more standardized evaluation of valvular disease.

4.5 Cardiovascular Risk Stratification and Prognosis

Beyond disease detection, machine-learning models are increasingly being investigated for cardiovascular risk prediction, prognosis, hospital readmission, and mortality assessment [8,13,56]. These models can integrate demographic, clinical, imaging, ECG, laboratory, and other data sources to generate individualized risk estimates [8,13]. Deep-learning algorithms have also been developed to predict in-hospital cardiac arrest using routinely collected vital signs [57]. However, their clinical usefulness depends not only on discrimination but also on calibration, external validation, and demonstration of benefit in the intended clinical setting [9,58].

To facilitate comparison across studies, Table 1 (Ref. [8,12,13,16,23,25,59]) summarizes representative applications of artificial intelligence in cardiovascular medicine according to clinical setting, input modality, model type, sample size, clinical task, validation strategy, major performance measure, and principal methodological limitations.

5. Limitations of Machine-Learning Models in Cardiovascular Disease

Despite their potential to improve diagnostic and prognostic performance, machine-learning models in cardiology face several important limitations. These include professional liability, systematic bias, privacy and surveillance concerns, cybersecurity risks, and technical and logistical challenges [3,60,61].

Clinical AI also creates specific privacy, cybersecurity, and governance requirements. Large-scale cardiovascular datasets may contain highly identifiable longitudinal, imaging, genomic, wearable, or physiologic information, making secure storage, access control, data minimization, and appropriate de-identification essential. AI systems may additionally be vulnerable to adversarial manipulation, unauthorized model access, model-inversion attacks, or extraction of sensitive training information. Institutions implementing cardiovascular AI should therefore establish clear accountability for data access, algorithm updates, incident reporting, audit trails, and clinical oversight. Governance structures should also specify who is responsible when model recommendations conflict with clinician judgment or when model performance deteriorates after deployment.

Many advanced ML models, particularly deep learning approaches, function as “black boxes”, making it difficult for clinicians to understand how decisions are made. This lack of transparency can hinder trust and acceptance among healthcare professionals [58,62,63].

Table 1. Representative artificial-intelligence studies in cardiovascular medicine.

Disease/clinical setting	Input data modality	Algorithm/model	Sample size	Clinical task	Validation strategy	Major performance metric	Principal limitation
General cardiovascular risk prediction—Alaa et al. (2019) [8]	Clinical and demographic data from UK Biobank; 473 variables	AutoPrognosis automated ML ensemble	423,604 participants	Prediction of 5-year cardiovascular disease risk	10-fold stratified cross-validation	AUC 0.774 (95% CI 0.768–0.780)	Developed and evaluated within the UK Biobank population; independent external validation was not performed
Heart failure with reduced ejection fraction—Kwon et al. (2019) [16]	12-lead ECG and demographic variables	Deep-learning ECG model	22,765 patients; 55,163 ECGs	Identification of HFrEF (LVEF ≤40%)	Internal and external validation using data from two hospitals	AUROC 0.843 internally and 0.889 externally	Retrospective ECG–echocardiography dataset; performance may vary across institutions, devices, and populations
Atrial fibrillation screening—Perez et al. (2019) [12]	Smartwatch photoplethysmography with confirmatory ECG patch	Irregular-pulse detection algorithm	419,297 participants	Detection of possible atrial fibrillation	Prospective large-scale pragmatic evaluation with ECG-patch confirmation	PPV 0.84 (95% CI 0.76–0.92) for simultaneous AF confirmation	Only a proportion of notified participants returned analyzable ECG patches; participants were self-selected smartwatch users
Left ventricular systolic dysfunction—Attia et al. (2022) [25]	Single-lead Apple Watch ECG	AI-ECG deep-learning algorithm	2454 participants; 421 had ECG–echocardiogram pairs for primary analysis	Detection of LVEF ≤40%	Prospective digital study; comparison with echocardiography	AUC 0.885 (95% CI 0.823–0.946)	Only 16 participants in the principal analysis had LVEF ≤40%, limiting precision and generalizability
Ischemic heart disease—Marzoog et al. (2024) [23]	Exhaled volatile organic compounds measured by PTR-TOF-MS	LASSO logistic regression with feature selection/ XGBoost	80 participants (31 IHD, 49 non-IHD)	Detection of stress-induced myocardial perfusion defect	Nested/leave-one-out cross-validation with CTP as reference standard	AUC 0.838; sensitivity 83.9%; specificity 77.6%	Small, single-center cohort without independent external validation
Advanced heart failure with renal dysfunction—Zhang et al. (2024) [13]	Electronic health record, laboratory, echocardiographic, and clinical variables	Hybrid survival ML framework (AIHFLevel; gradient boosting/ XGBoost-based survival models)	1736 patients (712 development/internal cohort; 1024 external cohort)	Prediction of all-cause mortality in advanced HF with renal dysfunction	Repeated 10-fold CV, Monte Carlo CV, bootstrap validation, and independent external validation	Average C-index 0.821 during model selection; external time-dependent AUC up to 0.846	Retrospective cohorts and a highly selected advanced-HF/ renal-dysfunction population may limit broader applicability

Table 1. Continued.

Disease/clinical setting	Input data modality	Algorithm/model	Sample size	Clinical task	Validation strategy	Major performance metric	Principal limitation
Coronary heart disease prediction—Demir et al. (2025) [59]	UCI Heart Disease and Framingham datasets; clinical and demographic variables	ML and DL models including XGBoost, kNN, SVM, ANN, CNN, and LSTM	UCI: 303 records; Framingham: 4240 records	CHD detection and 10-year CHD-risk classification	Random train–test splitting following preprocessing; comparison of multiple ML/DL models	Framingham: XGBoost accuracy 90.97%, AUC 90.9%; LSTM AUC 95.6%	Reliance on publicly available benchmark datasets and random splitting; no independent prospective clinical validation

ML, machine learning; AUC, area under the curve; CI, confidence interval; ECG, electrocardiogram; HFrEF, heart failure reduced ejection fraction; LVEF, left ventricular ejection fraction; AUROC, area under the receiver operating characteristic curve; PPV, positive predictive value; AF, atrial fibrillation; LASSO, least absolute shrinkage and selection operator; IHD, ischemic heart disease; CTP, stress computed tomography myocardial perfusion imaging; UCI, University of California; DL, deep learning; kNN, k-nearest neighbors; SVM, support vector machine; ANN, artificial neural network; CNN, convolutional neural network; LSTM, long short-term memory; CHD, coronary heart disease.

The performance of ML models heavily relies on the quality of the data used. Issues such as outdated or poorly selected data can introduce biases, leading to inaccurate predictions. Furthermore, historical biases present in datasets can perpetuate stereotypes and result in erroneous conclusions [64,65,66]. There is a risk that ML models may overfit to training data, performing well on known datasets but failing to generalize to new or unseen patient populations. This issue is particularly pronounced when models are trained on small or homogeneous datasets [62].

A further methodological concern is data leakage, which can produce substantially optimistic estimates of model performance. Leakage may occur when multiple ECGs, images, or encounters from the same patient are divided between training and testing sets, when feature selection or normalization is performed using the complete dataset before data splitting, or when variables containing information unavailable at the intended prediction time are included in model development. Cardiovascular AI studies should therefore use patient-level rather than record-level separation when repeated observations are present, perform preprocessing and feature selection within the training data, and use appropriately nested validation procedures for hyperparameter optimization. Temporal leakage should also be excluded when models are intended for prospective prediction.

Models developed using data from specific populations may not perform well when applied to different demographic groups due to variations in disease presentation or risk factors, necessitating careful validation across diverse patient groups [64].

Validation should be considered at several levels. Internal cross-validation or random hold-out testing evaluates reproducibility within the development population but does not establish generalizability. Temporal validation tests performance in patients treated at a later period, whereas geographic external validation evaluates the model in independent institutions or health systems. Performance should also be examined across relevant demographic and clinical subgroups. Changes in disease prevalence, referral patterns, acquisition devices, clinical practice, or patient characteristics may produce dataset or domain shift and cause substantial deterioration after deployment. Consequently, multicenter external validation followed by prospective evaluation in the intended clinical environment is an important prerequisite for routine implementation.

Reported model performance should also distinguish discrimination, calibration, and clinical utility. Discrimination describes how effectively a model separates patients with and without an outcome and is commonly quantified using the area under the receiver-operating-characteristic curve. Calibration assesses agreement between predicted and observed risks and may be examined using calibration plots, calibration intercept and slope, or prediction-error measures such as the Brier score. Neither good discrimination nor good calibration alone demonstrates clinical benefit. Clinical utility should therefore be examined using clinically meaningful operating thresholds, decision-curve or net-benefit analysis, and ultimately prospective studies evaluating whether use of the algorithm changes clinical decisions or patient outcomes.

Regulatory evaluation represents an additional challenge for clinical cardiovascular AI. Algorithms used for diagnosis, prognosis, or treatment recommendations may fall within regulatory frameworks for medical software or software as a medical device, depending on their intended use and jurisdiction. Evaluation should therefore consider not only initial model performance but also transparency regarding the intended population, version control, update procedures, human oversight, and mechanisms for reporting failures. Adaptive or periodically retrained systems pose particular challenges because changes made after deployment may alter safety and performance. Predefined change-management procedures, ongoing performance assessment, and post-deployment surveillance are therefore important components of responsible clinical implementation [3,9,63].

6. Current Challenges and Future Perspectives for Machine Learning in Cardiovascular Disease

Machine-learning technologies may improve efficiency and support clinical decision-making, but their implementation remains limited by concerns related to data privacy, interpretability, generalizability, workflow integration, and clinical validation [67]. Further research and multidisciplinary collaboration are needed before these tools can be adopted safely and effectively in routine cardiovascular practice [30,62,68,69].

Translation of an accurate algorithm into routine cardiovascular care requires more than technical validation. The model must fit the intended clinical workflow, provide information at a clinically useful time, communicate uncertainty appropriately, and operate without creating excessive alerts or additional workload. Integration with electronic health records, ECG management systems, imaging platforms, and clinical decision-support systems should be evaluated prospectively. Human oversight should remain explicit, particularly for high-risk decisions. Implementation studies should additionally assess usability, clinician acceptance, cost-effectiveness, failure modes, and whether algorithm-assisted care improves decisions or patient outcomes compared with usual care. Performance should continue to be monitored after deployment because changes in patient populations, devices, clinical pathways, or treatment practices can cause model drift [23].

7. Emerging AI Approaches and Future Directions

Cardiovascular AI is increasingly moving from disease-specific single-modality algorithms toward hybrid and multimodal systems capable of combining complementary information from ECGs, cardiovascular imaging, electronic health records, biomarkers, genomics, and wearable sensors [13,70]. Ensemble approaches may improve robustness by integrating predictions from different model classes, while transformer-based and foundation models offer the possibility of learning transferable representations from very large clinical datasets [9,13]. Generative AI may also support information extraction, multimodal summarization, and clinician–computer interaction. Nevertheless, greater model complexity does not necessarily imply greater clinical value. Emerging models require the same rigorous assessment of data leakage, calibration, external validation, fairness, interpretability, workflow impact, and clinical outcomes as conventional prediction models.

8. Discussion

Machine learning and deep learning are revolutionizing interventional cardiology by automating data analysis and improving diagnostic and prognostic prediction [30]. Machine learning shows promise in standardizing and improving cardiovascular pathology diagnoses, particularly in nonhuman animal models and basic science research [71]. In cardiovascular pathology, machine-learning-based computational image analysis has been applied to histological grading of cardiac allograft rejection using endomyocardial biopsy specimens [72]. However, challenges remain, including image quality standardization, consensus diagnosis, and the need for large, shared image databases. Addressing these challenges will unlock the full potential of ML in clinical cardiovascular pathology [67].

Artificial intelligence and machine learning have the potential to revolutionize healthcare, particularly in low- and middle-income countries (LMICs) where resources are scarce. While AI offers numerous benefits, including improved diagnosis and treatment, its implementation in LMICs requires a collective effort from various stakeholders to address systemic and individual challenges. Despite the potential, the effectiveness of AI in real-world practice remains to be fully established, and further research is needed to ensure its widespread adoption and impact on patient outcomes [73].

Explainable artificial intelligence may improve the transparency of cardiovascular prediction models by identifying features that contribute to individual or population-level predictions [58]. Feature-attribution methods, including SHAP values, can help clinicians examine model behavior and identify potentially implausible associations. However, post-hoc explanations should be interpreted cautiously, as feature importance does not necessarily indicate a causal relationship between a predictor and the clinical outcome. Furthermore, explainability alone does not establish model validity or clinical usefulness. Therefore, explanations should be evaluated for methodological reliability and clinical plausibility alongside rigorous model validation and assessment of clinical utility [9,58,63].

9. Conclusion

Artificial intelligence and machine-learning approaches are increasingly capable of extracting clinically relevant information from ECGs, cardiovascular imaging, electronic health records, wearable devices, and other biomedical data [74,75]. Nevertheless, high retrospective discrimination alone does not demonstrate clinical value. Data leakage, inadequate calibration, dataset shift, limited external and prospective validation, algorithmic bias, interpretability, privacy, cybersecurity, governance, and regulatory requirements remain important barriers to routine implementation. At present, cardiovascular AI should primarily complement rather than replace established diagnostic and prognostic standards, with clinicians retaining responsibility for patient-level decision-making. Future studies should prioritize transparent reporting, patient-level data separation, multicenter external validation, calibration and clinical-utility assessment, prospective workflow evaluation, and continuous post-deployment monitoring. Multimodal and hybrid AI approaches offer considerable potential, but their benefit should ultimately be judged by whether they improve clinical decisions and patient outcomes [6,76,77,78,79].

Abbreviations

CAD, coronary artery disease; AI, artificial intelligence; AF, atrial fibrillation; ANN, artificial neural network; AUC, area under the curve; AUROC, area under the receiver operating characteristic curve; CHD, coronary heart disease; CI, confidence interval; C-index, concordance index; CNN, convolutional neural network; CTP, stress computed tomography myocardial perfusion imaging; CV, cross-validation; DL, deep learning; ECG, electrocardiogram; HF, heart failure; HFrEF, heart failure with reduced ejection fraction; IHD, ischemic heart disease; kNN, k-nearest neighbors; LASSO, least absolute shrinkage and selection operator; LSTM, long short-term memory; LVEF, left ventricular ejection fraction; ML, machine learning; PPV, positive predictive value; PTR-TOF-MS, proton-transfer-reaction time-of-flight mass spectrometry; SVM, support vector machine; UCI, University of California, Irvine; XGBoost, extreme gradient boosting.

Author Contributions

DG, PC and PK literature searching, data curation, draft preparation, and reviewing the text of the manuscript for all the other authors. BM is the writer, researcher, collected and analyzed data, revised the final version of

the paper. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

Acknowledgment

Not applicable.

Funding

The work of Philipp Kopylov was financed by the government assignment 1023022600020-6 «Application of mass spectrometry and exhaled air emission spectrometry for cardiovascular risk stratification». The work of Basheer Marzoog was financed by the Priority 2030 program of the Ministry of Science and Higher Education of Russia, project «Screening of cardiac pathology using telemedicine technologies and elements of artificial intelligence», code: 03.000.B.163. The work of Basheer Marzoog was financed by the Priority 2030 program of the Ministry of Science and Higher Education of Russia, project «The Digital Cardiology with Artificial Intelligence», code: 03.000.B.166.

Conflicts of Interest

The authors declare no conflicts of interest.

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