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CONTACTS

Phone: **+998 50 737 87 88**

Website: <https://ist-journal.uz>

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CARDIOVASCULAR RISK ASSESSMENT IN THE ARAL SEA REGION USING ARTIFICIAL INTELLIGENCE MODELS

Uteuliev Niyetbay Uteulievich

Doctor of Physical and Mathematical Sciences, Professor
Head of the Department of Mathematical Modeling
Nukus State Technical University

Saytov Aralbek Umbetbaevich

Head of the Cardiology Department
Nukus City Medical Association

Saytov Kamiljan Begdullaevich

Assistant Lecturer, Department of Mathematical Modeling
Nukus State Technical University

Abstract: This study addresses intelligent cardiovascular risk assessment in cardiology inpatients from the Aral Sea region under incomplete and heterogeneous clinical-data conditions and proposes the CR-MRA algorithm as a solution. A retrospective analysis was conducted using anonymized clinical records of 2,039 patients treated at the Nukus City Medical Association during 2024–2026. The data demonstrated a substantial cardiorenal comorbidity burden together with irregular monitoring and heterogeneous clinical documentation. To reduce the influence of noisy clinical data on model decisions, a quality-aware adaptive formalization of CR-MRA (Cardio-Renal Medical Risk-Aware) was proposed. The algorithm combines, for each feature, a data-quality coefficient, data-driven relevance, and a regularized medical prior. The decision threshold is selected on validation data according to the F2-score. Recalculation of the available confusion matrix yielded a test size of $N=35,077$, with Recall=0.9747, Precision=0.6690, Accuracy=0.7433, Specificity=0.5066, F1=0.7934, and F2=0.8931. The findings indicate promising potential for sensitivity-oriented screening, while multicenter validation is planned to strengthen the evidence.

Keywords: artificial intelligence, cardiovascular diseases, patients from the Aral Sea region, CR-MRA algorithm, noisy clinical data, missing data, data quality, Recall, F2-score, screening.

Annotatsiya: Ushbu tadqiqot Orolbo'yi mintaqasidagi kardiologiya bo'limida davolanayotgan bemorlarda klinik ma'lumotlar to'liq bo'lmagan holatda ham va geterogenligi sharoitida yurak-qon tomir xavfini intellektual baholash masalasiga bag'ishlangan hamda ushbu muammoni hal etish uchun CR-MRA algoritmini taklif qiladi. 2024–2026-yillarda Nukus shahar tibbiyot birlashmasida davolangan 2039 nafar bemorning anonimlashtirilgan klinik ma'lumotlari asosida retrospektiv tahlil o'tkazildi. Ma'lumotlar kardiorenal komorbidlikning sezilarli darajada mavjudligini, shuningdek, monitoringning muntazam emasligi va klinik hujjatlarning geterogenligini ko'rsatdi. Shovqinli klinik ma'lumotlarning model qarorlariga ta'sirini kamaytirish maqsadida CR-MRA (Cardio-Renal Medical Risk-Aware) algoritmining ma'lumotlar sifatini hisobga oluvchi adaptiv formalizatsiyasi taklif qilindi. Algoritm har bir belgi uchun ma'lumotlar sifati koeffitsiyenti, ma'lumotlardan kelib chiqadigan relevantlik va regularizatsiyalangan tibbiy aprior koeffitsiyentni birlashtiradi. Qaror qabul qilish chegarasi validatsiya ma'lumotlari asosida F2-score ko'rsatkichi bo'yicha tanlandi. Mavjud chalkashlik matritsasini (confusion matrix) qayta hisoblash natijasida test to'plami hajmi $N = 35\,077$ bo'lib, quyidagi ko'rsatkichlar olindi: Recall = 0,9747, Precision = 0,6690, Accuracy = 0,7433, Specificity = 0,5066, F1 = 0,7934 va F2 = 0,8931. Olingan natijalar sezgirlikka yo'naltirilgan skrining uchun istiqbolli imkoniyatlarni ko'rsatadi, shu bilan birga dalillar bazasini mustahkamlash maqsadida ko'p markazli validatsiyani o'tkazish rejalashtirilgan.

Kalit so'zlar: sun'iy intellekt, yurak-qon tomir kasalliklari, Orolbo'yi mintaqasi bemorlari, CR-MRA algoritmi, shovqinli klinik ma'lumotlar, yetishmayotgan ma'lumotlar, ma'lumotlar sifati, Recall, F2-score, skrining.

Аннотация: Данное исследование посвящено интеллектуальной оценке сердечно-сосудистого риска у стационарных пациентов кардиологического профиля из Приаральского региона в условиях неполных и неоднородных клинических данных и предлагает алгоритм CR-MRA в качестве решения данной задачи. Проведён ретроспективный анализ анонимизированных клинических данных 2039 пациентов, проходивших лечение в Нукусском городском медицинском объединении в период 2024–2026 годов. Полученные данные продемонстрировали значительную кардиоренальную коморбидную нагрузку, а также нерегулярность

мониторинга и неоднородность клинической документации. Для снижения влияния зашумлённых клинических данных на решения модели предложена адаптивная формализация алгоритма CR-MRA (Cardio-Renal Medical Risk-Aware), учитывающая качество данных. Для каждого признака алгоритм объединяет коэффициент качества данных, релевантность, определяемую на основе данных, и регуляризованный медицинский априорный коэффициент. Порог принятия решения выбирался на валидационных данных в соответствии с показателем F2-score. Повторный расчёт на основе имеющейся матрицы ошибок показал размер тестовой выборки $N=35\,077$ и следующие показатели: Recall=0,9747, Precision=0,6690, Accuracy=0,7433, Specificity=0,5066, F1=0,7934 и F2=0,8931. Полученные результаты свидетельствуют о перспективности применения метода для скрининга, ориентированного на высокую чувствительность, при этом для усиления доказательной базы планируется проведение многоцентровой валидации.

Ключевые слова: искусственный интеллект, сердечно-сосудистые заболевания, пациенты Приаральского региона, алгоритм CR-MRA, зашумлённые клинические данные, пропущенные данные, качество данных, Recall, F2-score, скрининг.

INTRODUCTION

Cardiovascular diseases remain among the leading causes of death and disability worldwide [1]. Artificial intelligence and machine-learning methods can identify complex relationships in clinical data, support risk stratification, and assist clinical decision-making. In Uzbekistan, research at the intersection of cardiology and medical artificial intelligence is developing in electrocardiography, ischemic heart disease, and clinical prediction [2–4].

The development of artificial intelligence (AI) and machine learning (ML) has created new opportunities for cardiovascular risk assessment. AI-based models can process large numbers of clinical variables, identify nonlinear relationships, and detect complex patterns that may not be readily captured by conventional statistical methods. Applications of AI in cardiology include disease classification, electrocardiographic analysis, prediction of cardiovascular events, risk stratification, medical imaging, and clinical decision support. Nevertheless, successful implementation of AI in clinical practice requires consideration not only of predictive performance but also of data quality, clinical interpretability, population specificity, and robustness under real-world conditions.

These challenges are particularly relevant to patients from the Aral Sea region. The region represents a distinctive clinical and environmental context characterized by substantial long-term socioeconomic and environmental changes. Healthcare institutions serving this population may encounter patients with multiple chronic diseases and varying levels of diagnostic and monitoring documentation. Consequently, clinical datasets obtained from routine hospital practice may contain missing values, inconsistent measurements, irregular follow-up information, and heterogeneous documentation patterns. Such characteristics can affect the reliability of AI models and may lead to unstable or clinically inappropriate predictions if data quality is not explicitly considered.

REVIEW OF LITERATURE ON THE SUBJECT

Previous work relevant to cardiovascular artificial intelligence in Uzbekistan has progressed from general medical-AI development to disease-specific cardiovascular applications. Azimova et al. [3] described early directions of artificial intelligence in medicine in Uzbekistan, while Uzokov et al. [2] discussed its potential for ischemic heart disease. The 2026 multicenter EMR Score study further demonstrated the value of combining physiological signals with clinical risk information for coronary artery disease assessment [4].

From a methodological perspective, cardiorenal interactions are important because cardiac and renal dysfunction may reinforce each other [5]. For prediction systems based on heterogeneous clinical records, this creates a need to consider both the medical relevance of a variable and the reliability of the recorded value. At the same time, TRIPOD+AI and PROBAST+AI emphasize transparent development, separation of model development from final testing, and careful assessment of model applicability and bias [10,11].

However, real electronic medical records differ substantially from ideal research datasets. Laboratory measurements may be unavailable for some patients, monitoring may be performed at different frequencies, clinical notes may not follow a uniform format, and some examinations may not have been performed. In such conditions, simple imputation and static feature weighting may not fully reflect the reliability of individual clinical variables. Therefore, linking feature relevance to data quality is an important methodological task for real clinical systems.

This study analyzes a clinical cohort of 2,039 patients from the Aral Sea region treated at the Nukus City Medical Association. The observed comorbidity proportions therefore characterize a selected inpatient cardiology cohort and are not interpreted as population prevalence. The aim of the study is to extend the existing MRA-FW concept by incorporating data quality, mathematically formalize the CR-MRA algorithm to

account for missingness, anomalous values, and clinical inconsistencies, and reassess the pilot experimental results for internal numerical consistency.

RESEARCH METHODOLOGY

Local clinical cohort. The retrospective analysis included anonymized clinical records of 2,039 inpatients treated at the Nukus City Medical Association during 2024–2026. The mean patient age was 61.1 years. Diagnoses, medical history, arterial blood pressure, laboratory indicators, and the availability of selected instrumental examinations were evaluated (Table 1).

Table 1. Clinical conditions and data-quality issues recorded in N=2,039 cardiology inpatients¹

Clinical indicator / diagnosis	Count	Proportion	Data-quality description
History of myocardial infarction / ACS	2 037	99.9%	Timing and episodes in the medical history were not recorded with the same level of detail
History of stroke / CVA / TIA	1 966	96.4%	Neurological conclusions were incomplete in some records
Chronic kidney disease / nephropathy	1 951	95.7%	Creatinine and urea were not available in all records
Arterial hypertension	1 945	95.4%	Blood-pressure monitoring was irregular
Chronic heart failure	1 896	93.0%	NYHA functional class was not recorded in a uniform format
Ischemic heart disease	1 818	89.2%	Coronary angiography was not performed in all patients
Cardiac rhythm disorders	1 481	72.6%	Holter monitoring was not available for all patients
Anemia	963	47.2%	Hemoglobin was missing in some records
Type 2 diabetes mellitus	436	21.4%	Longitudinal glucose measurements were incomplete in some records

The high proportions shown in the table characterize the clinical selection of patients admitted to a specialized inpatient cardiology setting.

External experimental dataset and validation design. Machine-learning experiments used the open Cardiovascular Disease dataset containing 70,000 records [12]. The dataset includes age, sex, height, weight, systolic and diastolic blood pressure, cholesterol, glucose, smoking, alcohol consumption, physical activity, and the binary cardio target. The experimental design uses 5-fold stratified cross-validation with random_state=42 and a 20% inner-validation subset within each training fold; the threshold is selected in the 0.10–0.90 range according to the F2-score. The same design is applied consistently to CR-MRA.

All preprocessing, feature-relevance estimation, data-quality coefficients, prior regularization, feature selection, and threshold selection are determined using the training/validation data only. The test set is reserved for final unbiased evaluation. This design is consistent with the transparent validation principles described in TRIPOD+AI and PROBAST+AI [10,11].

Formalization of the data quality index. In CR-MRA, data quality is represented through three principal components: missingness, anomalous values, and clinical/logical inconsistencies. For each feature i , these proportions are defined as follows:

$$M_i = \frac{N_i^{miss}}{N_i} \quad (1)$$

$$O_i = \frac{N_i^{out}}{N_i} \quad (2)$$

$$C_i = \frac{N_i^{inc}}{N_i} \quad (3)$$

¹ Source: Author's own work.

Here, M_i is the proportion of missing values, O_i is the proportion of values outside predefined physiological or robust statistical limits, and C_i is the proportion of clinical or logical inconsistencies.

$$Q_i = 1 - \lambda_M M_i - \lambda_O O_i - \lambda_C C_i, \quad \lambda_M + \lambda_O + \lambda_C = 1 \quad (4)$$

A value of $Q_i=1$ indicates high-quality information for the feature, whereas $Q_i=0$ indicates reduced reliability of the corresponding clinical data. The λ coefficients are selected during training/validation rather than on the test set.

Data-driven relevance and regularized medical prior. For each feature, model-based feature importance I_i and statistical relevance S_i are normalized to the $[0,1]$ interval. The normalized values are denoted by I_i^{norm} and S_i^{norm} . Mutual information or another predefined training-only criterion may be used as the statistical relevance measure. The overall data-driven relevance is:

$$D_i = \frac{I_i^{norm} + S_i^{norm}}{2} \quad (5)$$

To improve the stability of the signal obtained from local clinical data, the local prior is balanced against the global medical prior through a shrinkage mechanism:

$$\rho_i = \frac{n_i}{n_i + \kappa} \quad (6a)$$

$$R_i^{reg} = \rho_i R_i^{local} + (1 - \rho_i) R_i^{global} \quad (6b)$$

Here, n_i is the number of reliable local observations for feature i , and $\kappa > 0$ is a regularization hyperparameter. The sources of the local and global priors and the value of κ are documented in the experimental protocol to support reproducibility.

Core Adaptive Weighting Rule of CR-MRA. The central idea of CR-MRA is to rely more strongly on data-driven signals when data quality is high and more strongly on the regularized clinical prior when data quality decreases. The final integrated score is:

$$W_i = Q_i D_i + (1 - Q_i) R_i^{reg} \quad (7)$$

If $Q_i \approx 1$, then $W_i \approx D_i$; if $Q_i \approx 0$, then $W_i \approx R_i^{reg}$. Thus, CR-MRA differs from MRA-FW not merely by name, but by an additional mechanism in which feature reliability directly influences the decision process.

The final feature weights are normalized using Softmax:

$$w_i = m \cdot \frac{\exp(W_i / T)}{\sum_{j=1}^m \exp(W_j / T)} \quad (8)$$

Here, m is the number of features and $T > 0$ is the Softmax temperature. The multiplier m keeps the mean feature weight approximately around 1.

Missingness Mask. To allow the model to distinguish an imputed value from an actual measurement, an availability mask m_{ji} is introduced for each patient j and feature i :

$$m_{ji} = \begin{cases} 1, & x_{ji} \text{ is available,} \\ 0, & x_{ji} \text{ is missing.} \end{cases} \quad (9a)$$

$$x_{ji}^w = m_{ji} \cdot w_i \cdot z_{ji} \quad (9b)$$

Providing the missingness mask together with the weighted features allows the classifier to distinguish an actual observation from a value filled by imputation.

F2-Score and decision threshold. Because false-negative cases are important in screening, Precision and Recall are evaluated jointly. F2-score gives greater weight to Recall than F1-score:

$$P = \frac{TP}{TP + FP} \quad (10a)$$

$$R = \frac{TP}{TP + FN} \quad (10b)$$

$$F_2 = \frac{5PR}{4P + R} \quad (11)$$

The optimal threshold is selected on validation data according to the following rule:

$$\tau_{\text{opt}} = \arg \max_{\tau \in \Theta} F_2(\tau) \quad (12)$$

The test set is not used to select the threshold or other hyperparameters. In the pilot experiment, $\tau=0.22$ was recorded as the optimal threshold; this value will be re-evaluated in subsequent reproducible runs using the same validation protocol.

ANALYSIS AND RESULTS

The local retrospective analysis showed that cardiorenal and other comorbid conditions were recorded at high proportions in the selected inpatient cohort. These findings characterize the clinical profile of the specialized cardiology inpatient cohort (Figure 1).

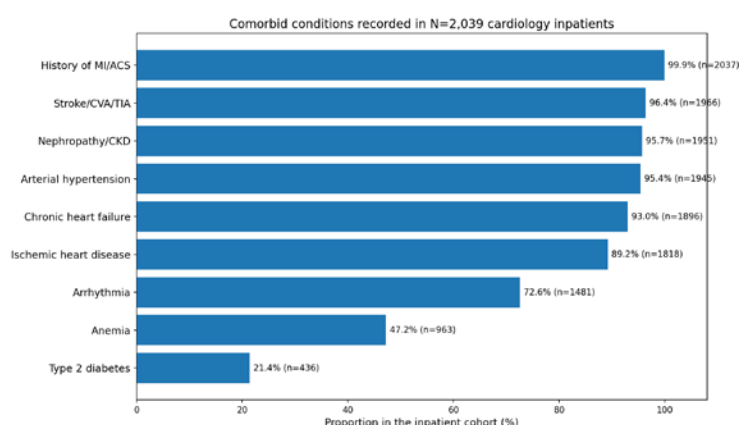


Figure 1. Proportions of comorbid conditions recorded in N=2,039 cardiology inpatients²

Figure 1 presents the clinical profile of 2,039 patients treated in the specialized inpatient setting. The high values indicate a substantial cardiorenal comorbidity burden in the selected cohort and provide additional information for cautious formulation of regional clinical priors in CR-MRA (Table 2).

Table 2. Experimental comparison of model performance in a noisy clinical-data setting³

Model / algorithm	Threshold τ	Accuracy	Recall	F2-score
Logistic Regression	0.50	71.2%	66.4%	0.672
Random Forest	0.50	72.4%	69.1%	0.697
XGBoost	0.50	73.1%	70.5%	0.710
Baseline MRA-FW	0.50	72.8%	68.3%	0.691
CR-MRA (pilot)	0.22	74.3%	97.47%	0.8931

The CR-MRA F2-score in Table 2 was refined to 0.8931 on the basis of the confusion matrix. The comparison with baseline models was organized using the same preprocessing, seed, and split protocol; the results are intended to be strengthened further with reproducible code and run logs (Figure 2).

² Source: Author's own work.

³ Source: Author's own work.

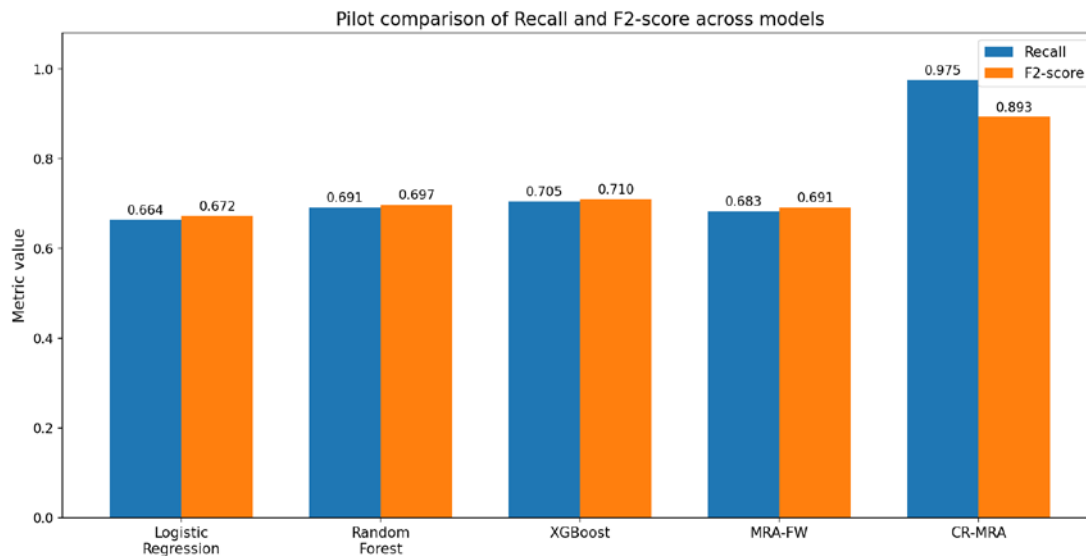


Figure 2. Experimental comparison of Recall and F2-score for the baseline models and CR-MRA⁴

Figure 2 shows that CR-MRA has higher Recall and F2-score in the pilot comparison. This sensitivity-oriented operating point is intended to reduce missed positive cases. In the next stage, repeated cross-validation and confidence intervals can be added to characterize the stability of the results more comprehensively.

The confusion matrix reported in the pilot results is TP=17,290, FN=449, FP=8,555, and TN=8,783. The sum of these four elements is N=35,077:

$$N = TP + FN + FP + TN = 35077 \quad \text{Recall} = \frac{TP}{TP + FN} = \frac{17290}{17290 + 449} = 0.9747$$

$$\text{Precision} = \frac{TP}{TP + FP} = \frac{17290}{17290 + 8555} = 0.6690 \quad \text{Accuracy} = \frac{TP + TN}{N} = \frac{17290 + 8783}{35077} = 0.7433$$

$$\text{Specificity} = \frac{TN}{TN + FP} = \frac{8783}{8783 + 8555} = 0.5066 \quad F_1 = 0.7934, \quad F_2 = 0.8931$$

With baseline MRA-FW Recall=0.683 and 17,739 actual positive cases, the number of false negatives is approximately 5,623. In CR-MRA, this value decreases to 449, corresponding to an approximately 12.5-fold reduction in false-negative cases.

The principal distinction of CR-MRA is the direct inclusion of a data-quality component in feature weighting. MRA-FW combines feature importance, statistical relevance, and a medical prior, whereas CR-MRA additionally incorporates the reliability coefficient Q_i . Consequently, the model relies more strongly on data-driven evidence for complete and reliable features, while the relative contribution of the regularized clinical prior increases as data quality decreases.

In the pilot confusion matrix, Recall=0.9747, Specificity=0.5066, and Precision=0.6690. These values indicate that CR-MRA is oriented toward sensitivity-focused screening: broader coverage of positive cases may be accompanied by an increase in the number of patients referred for additional examination. Therefore, comprehensive assessment of model performance should include Precision, Specificity, F1, F2, AUROC, AUPRC, calibration, and decision-curve analysis.

When formulating local clinical priors, the frequency observed in the cohort is used as an additional clinical signal rather than as the sole criterion. Regularization creates a balance between R_i^{local} and R_i^{global} , while subsequent sensitivity analysis can further characterize the influence of the priors.

4 Source: Author's own work.

CONCLUSIONS AND SUGGESTIONS

Extending the findings obtained from the inpatient cohort to primary care facilities and other clinical environments represents an important direction for the further development of the CR-MRA model. Validation using geographically and temporally independent datasets would provide stronger evidence of the model's reliability, generalizability, and stability across different patient populations and healthcare settings. In addition, evaluating the model under varying clinical conditions could help identify potential limitations related to data availability, patient characteristics, and differences in clinical documentation practices. In Uzbekistan, the 2026 EMR Score study, which combined seismocardiography with clinical risk factors, provides a methodological example of a multicenter approach to cardiovascular risk assessment [4].

Building on this experience, future research could focus on evaluating CR-MRA across multiple healthcare institutions, comparing its performance with established prediction models, and assessing its clinical utility under real-world conditions. Such investigations would help determine whether the integration of data-quality indicators into feature weighting improves the consistency of predictions and supports more reliable cardiovascular risk stratification. Ultimately, comprehensive external validation and prospective clinical evaluation would be essential steps toward establishing the practical applicability of CR-MRA and supporting its potential integration into clinical decision-support systems in Uzbekistan.

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