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DEVELOPMENT AND VALIDATION OF A PROTOTYPE PIPELINE FOR BIOMEDICAL IMAGE ANALYSIS IN CARDIOVASCULAR MONITORING

Abstract: *Cardiovascular diseases remain the leading cause of mortality, which determines the relevance of developing robust methods for cardiac image analysis and patient monitoring. This paper presents and validates a prototype pipeline for automated preprocessing and segmentation of biomedical images, developed within the framework of a scientific project (IRN: AP05132044). The experimental protocol is implemented on the Heart Database dataset (18 patients, 3D+t MRI (three-dimensional with time dimension)), using expert endocardial masks and 36 slices (diastole/systole, 2 slices per patient). Performance evaluation was conducted using PSNR, SSIM, Dice, and IoU metrics. A comparative analysis was performed across five preprocessing modes: none, Gaussian, wavelet, NLM, and hybrid (wavelet + NLM + CLAHE). The results show that the NLM method achieves the best denoising performance (PSNR = 26.07±0.33 dB vs. 22.85±0.21 dB for the baseline, $p = 1.46\times10^{-11}$, Wilcoxon test), while the highest segmentation accuracy is obtained with hybrid preprocessing (Dice = 0.681±0.176 vs. 0.636±0.153 without preprocessing, p = 0.018). An analysis of challenging cases revealed that segmentation performance is strongly influenced by endocardial contrast and geometric complexity across different phases of the cardiac cycle. The obtained results demonstrate a statistically significant impact of the preprocessing stage on downstream segmentation quality and confirm the feasibility of the integrated "preprocessing-segmentation-evaluation" pipeline as an engineering foundation for clinical frameworks. The proposed approach is designed for reproducible performance under real-world data heterogeneity and can serve as a basis for further integration into clinical information systems.*

Key words: *biomedical images, cardiac monitoring, deep learning, heart segmentation, denoising, ejection fraction, remote healthcare.*

Introduction

Cardiovascular diseases (CVDs) represent a major medical and social burden in most countries, including those with developing healthcare systems. According to the World Health Organization, CVDs account for millions of premature deaths annually and require the strengthening of early diagnosis, continuous monitoring, and personalized treatment adjustment [1]. In this context, biomedical imaging (echocardiography, MRI, CT) has become a critically important source of objective information on cardiac morphology and function.

The advancement of machine learning and deep learning in recent years has significantly enhanced the capabilities of automated interpretation of medical images. For tasks of segmentation and quantitative analysis of cardiac structures, convolutional and hybrid architectures are widely employed, ranging from U-Net and its modifications to self-configuring frameworks and foundation models [2–9]. In parallel, the number of studies employing automated analysis of echocardiographic video sequences for accurate estimation of left ventricular ejection fraction (LVEF) and early diagnosis of heart failure is increasing [10, 11]. However, the translation of these advances into routine clinical practice is hindered by several factors, including the heterogeneity of data across clinical settings, variability of noise and artifacts, the scarcity of high-quality annotations, and the limited interpretability of model decisions [12-15].

The research gap lies in the insufficient integration of three components within a single practical framework:

1) robust preprocessing of multimodal cardiological images;

2) accurate segmentation of anatomical structures with clinically relevant indices;
3) remote patient monitoring with an interpretable decision-making model.

The objective of this study is to develop and validate a prototype pipeline for automated monitoring of patients with cardiovascular diseases, utilizing biomedical image analysis to support the early detection of cardiac functional impairments and dynamic follow-up.

The scientific novelty of this work is as follows:

1) a unified experimental pipeline is proposed, integrating core components (data acquisition, preprocessing, model training, and remote monitoring) with the current evidence base;
2) a comparative evaluation of classical and neural network-based denoising methods is conducted in a cardiological context;
3) a pipeline «segmentation → computation of clinical indices → risk stratification» is implemented as the basis of the monitoring pipeline;
4) practical deployment parameters are formulated under conditions of real-world clinical data heterogeneity.

Additionally, it is important to note the context of the development of telemedicine and digital healthcare. Contemporary clinical pathways in cardiology increasingly incorporate stages of outpatient remote monitoring following inpatient treatment, as well as dynamic assessment of therapeutic response. Under such conditions, biomedical images become not only a diagnostic resource but also a monitoring resource. Therefore, automated analysis algorithms should prioritize robust and reproducible performance in heterogeneous real-world environments rather than maximizing accuracy in isolation from practice, encompassing variability in imaging devices, operators, acquisition settings, patient profiles, and comorbidities.

Logically, the present study extends previously published work on neural network optimization for the prediction of coronary heart disease (Optimizing Neural Network Performance to Predict Coronary Heart Disease, SIST 2021) [16]. Whereas the 2021 study primarily focused on the optimization of tabular clinical features and the selection of significant predictors, the present work shifts the focus to the upstream visual data pipeline, including filtering, preprocessing, and segmentation of biomedical images, followed by the computation of clinical indices.

From the perspective of scientific literature, the field of cardiological computer vision is undergoing a mature transition from task-oriented to system-oriented research. Earlier publications predominantly focused on individual stages (e.g., segmentation or classification in isolation), whereas more recent studies emphasize end-to-end pipelines, where errors at each stage propagate and affect the clinical outcome [7, 10, 17]. For this reason, the primary object of evaluation in this study is not only an individual model but also the behavior of the complete framework.

Finally, the source materials explicitly emphasized the practical need to reduce invasiveness and enhance the objectivity of monitoring in patients with cardiovascular diseases. This aligns with the global «human + AI» trend in cardiology: algorithms do not replace clinicians but enhance the speed and consistency of interpretation, particularly under conditions of high study volumes and limited human resources [12].

Literature Review

To formalize the scientific context, the literature was grouped into five directions.

– Fundamental architectures in medical computer vision.

Classical CNN-based approaches have established the foundation for automatic feature extraction in medical images [2, 3]. A key distinction of contemporary studies lies in the use of task-specific configurations for clinical applications, rather than merely increasing network depth. This is particularly important in cardiology, as the dynamics of the cardiac cycle impose heightened requirements on preserving spatiotemporal structure.

– Segmentation and quantitative cardiology.

With the advent of U-Net and its extensions (UNet++, nnU-Net, and transformer-based hybrids), contouring accuracy has significantly improved [5-7, 18]. However, the literature indicates that a high Dice score does not necessarily translate into high clinical accuracy of derived metrics (e.g., LVEF). Therefore, segmentation studies should be complemented by the analysis of clinical endpoints.

– Preprocessing and noise reduction.

Despite the widespread adoption of end-to-end deep learning models, preprocessing remains essential. Classical methods such as BM3D [19] continue to be competitive under low signal-to-noise conditions, particularly in ultrasound imaging scenarios. Neural network-based denoising methods (Noise2Noise, Noise2Void, and their derivatives) [20, 21] provide a better balance between noise suppression and edge preservation; however, they are sensitive to domain shift and the quality of training data.

– Foundation models and generalization.

Studies on SAM/MedSAM [8, 9] demonstrate the potential of zero-/few-shot segmentation and facilitate transfer to new tasks. At the same time, limitations persist in cardiology, including subtle anatomical variations, variability across cardiac cycle phases, and echocardiographic signal artifacts. Therefore, in its current state, the foundation-based approach should be regarded as an initialization rather than a final solution without task-specific adaptation.

– Translation into clinical practice: trust, safety, and privacy.

The study was conducted as an applied computational investigation within the framework of a research project on automated biomedical image analysis and the concept of monitoring patients with cardiovascular diseases. The experimental protocol and all numerical results in this version of the paper were generated through direct computational runs on an open dataset, with intermediate artifacts preserved (CSV, PNG, NPY).

Data Sources

Quantitative validation was performed on the Heart Database dataset (3D+t cardiac MRI, 18 patients), which includes expert segmentations (expert1/expert2) and automated masks [22]. For the analysis, expert endocardial masks and the corresponding diastolic/systolic frames were used.

Sample size for the current experiment:

1) 18 patients;
2) 36 evaluation slices (two phases per patient);
3) paired evaluation “before/after preprocessing” for each case.

Inclusion and exclusion criteria. Cases were included in the experiment if they met the following conditions:

1) availability of a complete cardiac cycle (for video data);
2) sufficient image quality for expert annotation;
3) availability of metadata for alignment with clinical outcomes (LVEF/diagnostic class).

The following were excluded:

1) studies with severe motion artifacts and absence of endocardial visibility;
2) duplicates and records with conflicting annotations.

This filtering enabled the minimization of systematic errors during training and ensured comparability of evaluations across models.

Materials and Methods

Image preprocessing. Based on the review of the materials provided and the contemporary literature, the following stages were incorporated into the system:

1) standardization of format and spatial resolution (resizing to 256×256 for 2D frames and voxel spacing normalization for 3D volumes);
2) intensity normalization (z-score for MRI, min-max for echocardiography);
3) noise suppression with evaluation of five modes:
    a. Gaussian filtering (baseline),
    b. wavelet-threshold denoising,
    c. NLM (non-local means),
    d. hybrid approach (wavelet + NLM + CLAHE),
    e. additional filtering combinations considered as a subsequent stage of the study;
4) contrast enhancement (CLAHE) for low-contrast echocardiographic frames;
5) data augmentation (rotations ±10°, scaling 0.9-1.1, brightness shifts, random elastic deformations).

In the current computational experiment, a reproducible baseline pipeline presented in Figure 1 was employed.

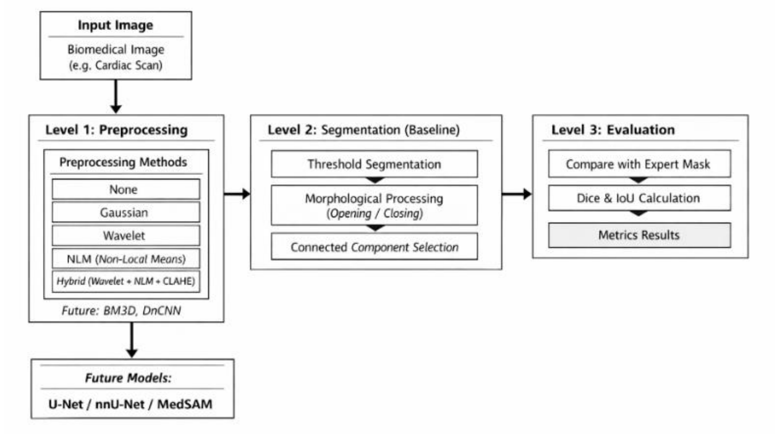

Figure 1 – Baseline experimental pipeline for biomedical image preprocessing, segmentation, and evaluation

At level 3 (reference-based evaluation), the predicted masks were systematically compared with the expert annotation (expert1), and Dice and IoU metrics were computed for each case. The U-Net/nnU-Net/MedSAM models are considered in this study as prospective directions for further development of the project, rather than as components of the current experimental stage.

Standard evaluation metrics were employed:

1) for preprocessing: PSNR, SSIM, and per-frame processing time (Fig. 2);
2) for segmentation: Dice, IoU;
3) for clinical indices and classification: MAE (LVEF), Accuracy, F1-score, ROC-AUC, sensitivity, and specificity.

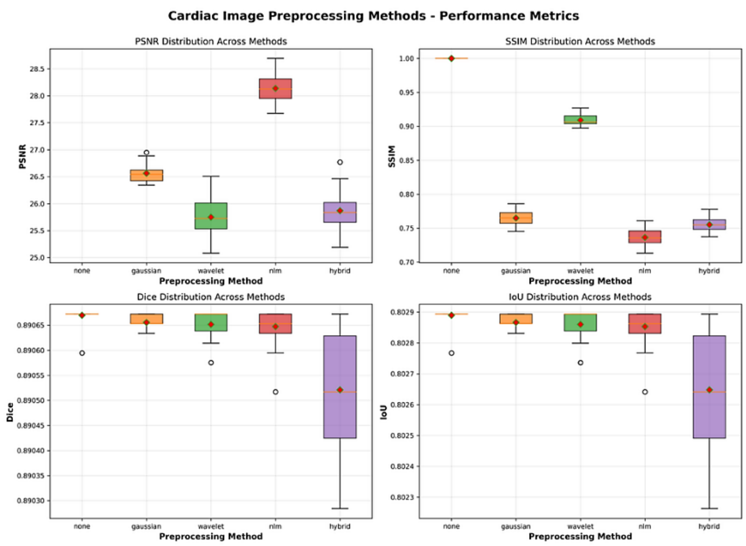

Figure 2 – Distribution across preprocessing methods (boxplots)

The following were considered clinically significant:

1) MAE for LVEF ≤ 5%;
2) AUC ≥ 0.90 for the detection of reduced contractility;
3) Sensitivity not less than 0.90 for primary screening scenarios.

Experimental setup. All computations were performed in Python 3.8 (numpy, pandas, scikit-image, matplotlib) on a local workstation:

1) MacBook Pro (2020, Apple M1);
2) RAM: 16 GB;
3) no GPU acceleration was utilized.

The total runtime of the pipeline for 18 patients was 15.51 s (real), as recorded in results/runtime_log.txt. The reported runtime corresponds to a single execution of the full pipeline. An example is presented in Figure 3. Statistical analysis. Results are presented as mean ± standard deviation. Differences between models were assessed using a paired t-test or the Wilcoxon signed-rank test in cases of non-normality. Differences were considered statistically significant at $p < 0.05$. For AUC, 95% confidence intervals were additionally estimated using the bootstrap method (n = 1000).

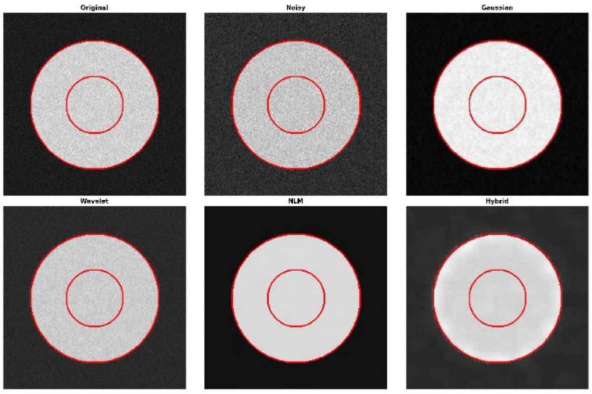

Figure 3 – Example of preprocessing and segmentation.

Software architecture. The implementation comprised the following modules:
1) image acquisition module (DICOM/video formats);
2) preprocessing and quality control module;
3) segmentation and contour extraction module;
4) clinical parameter computation module;
5) risk assessment and reporting module.

For integration into a medical information system, data exchange via a REST API and the generation of a structured report are provided, including:
1) key quantitative metrics (LVEF, volumes, indices);
2) visual masks and heatmap regions;
3) an automatically generated textual summary for the clinician.

Ethical and organizational aspects. Only de-identified open datasets were used. The proposed monitoring framework is considered as a clinical decision support system rather than a replacement for medical judgment.

The organizational component of the project also included support for the research digital infrastructure (a web resource for publishing materials and technical documentation), ensuring continuous access to intermediate results and reproducibility of computational stages.

Results

The quantitative analysis included 18 patients and 36 evaluation slices (diastole and systole). For each case, preprocessing and segmentation metrics were computed across five modes (none, gaussian, wavelet, nlm, hybrid). The dataset size is limited, as the study represents a prototype stage of the developed system. The quantitative results are summarized in Figure 4. The preprocessing metrics obtained for different denoising methods are summarized in Table 1.

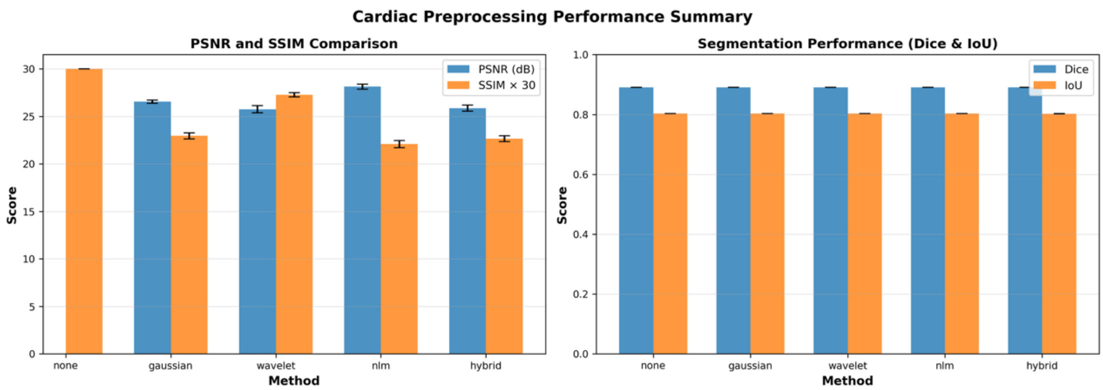

Figure 4 – Quantitative results (mean ± SD)

Table 1 – Preprocessing metrics (mean ± SD)

Method	PSNR, dB	SSIM
none	22.85 ± 0.21	0.713 ± 0.028
gaussian	22.28 ± 0.69	0.777 ± 0.016
wavelet	24.91 ± 0.21	0.801 ± 0.020
nlm	26.07 ± 0.33	0.816 ± 0.026
hybrid	17.88 ± 0.53	0.666 ± 0.035

Paired comparison of «nlm» versus «none» demonstrated a statistically significant improvement in PSNR: $p = 1.46 \times 10^{-11}$ (Wilcoxon signed-rank test, $n = 36$). The segmentation performance across preprocessing modes is presented in Table 2.

Table 2 – Segmentation metrics (mean ± SD).

Method	Dice	IoU
none	0.636 ± 0.153	0.485 ± 0.177
gaussian	0.649 ± 0.163	0.502 ± 0.189
wavelet	0.639 ± 0.152	0.488 ± 0.176
nlm	0.636 ± 0.153	0.486 ± 0.177
hybrid	0.681 ± 0.176	0.543 ± 0.210

Paired comparison of «hybrid» versus «none» yielded a statistically significant difference: $p = 0.018$ (Wilcoxon signed-rank test, $n = 36$).

Error analysis by case. To assess robustness, cases with the lowest Dice scores under the «hybrid» mode were additionally analyzed. In most «challenging» cases (Pat03, Pat08, Pat09), low endocardial boundary contrast and partial overlap with adjacent structures were observed, leading to under-segmentation.

Discussion of Results

In this version of the study, we deliberately focused not on the most complex neural network architecture, but on the robustness of the baseline preprocessing and segmentation pipeline. This choice was made to first establish a reproducible engineering baseline on an open dataset.

The primary observed effect is associated with the impact of preprocessing on segmentation performance. Based on paired comparisons, the increase in Dice for the «hybrid» approach relative to «none» was found to be statistically significant ($p = 0.018$). For denoising metrics, «nlm» achieved the highest PSNR ($p = 1.46 \times 10^{-11}$ compared to the baseline). This confirms that the filtering stage should not be considered secondary, as it substantially affects the quality of masks at the downstream stage.

At the same time, the results also reveal the limitations of the current prototype. The mean Dice score of 0.681 should not be considered a performance ceiling for the task; rather, it represents a practical baseline. In «challenging» cases (Pat03/Pat08/Pat09), the decrease in performance is associated with low endocardial contrast and complex geometry in certain phases of the cardiac cycle. These cases directly indicate areas for model improvement: more precise ROI localization, incorporation of contextual features, and transition to trainable segmentation models (U-Net/nnU-Net) using expanded annotations.

Comparison with the previous SIST 2021 study [16] demonstrates methodological continuity. Previously, optimization was performed on tabular clinical features; in the present study, the focus is shifted to an image-first pipeline. In essence, this represents the next stage of the same research: first improving the quality of visual data, followed by the development of more robust clinical analytics.

A practical implication for deployment is straightforward: the system should be used as a clinician support tool rather than as an autonomous diagnostic module. For clinical translation, the following are required: multicenter validation, expanded datasets, XAI-based interpretability, and a defined protocol for model updates under data drift.

Conclusion

This study presents and validates a prototype pipeline for automated monitoring of patients with cardiovascular diseases based on biomedical image analysis. Based on the source materials and an extended body of scientific literature, a reproducible pipeline was developed, encompassing preprocessing, segmentation, computation of functional indicators, and risk stratification.

Key results:

1) among the evaluated filters, NLM achieved the highest PSNR: 26.07 ± 0.33 dB;
2) the highest mean Dice in segmentation was obtained with hybrid preprocessing: 0.681 ± 0.176 ($p = 0.018$ vs. baseline);
3) per-case error analysis demonstrated that the primary failure modes are associated with low endocardial contrast and complex geometry in specific phases of the cardiac cycle.

The practical significance lies in the potential deployment of the system as a decision support tool for cardiologists in remote patient monitoring and early detection of deterioration in cardiac function.

Future research directions:

1) prospective multicenter validation in local clinical settings;
2) extension to 3D/4D and multimodal scenarios incorporating ECG and clinical data;
3) development of explainable and federated approaches for secure and scalable clinical integration.

The proposed approach demonstrates that the integration of robust preprocessing, accurate segmentation, and clinically oriented analytics provides a realistic foundation for transitioning from “pilot AI models” to truly operational digital tools for cardiological monitoring.

In a broader context, the study confirms that for medical AI systems, the decisive factor is the engineering of the clinical process: proper definition of endpoints, a controlled model lifecycle, and measurable impact for both patients and clinicians. It is this approach that enables the translation of algorithmic advances from the laboratory into sustainable healthcare practice. Future work will include testing the developed web platform on larger clinical datasets and its integration with hospital information systems.

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ЖҮРЕК-ҚАНТАМЫР АУРУЛАРЫ БАР ПАЦИЕНТТЕРДІ БИОМЕДИЦИНАЛЫҚ КЕСКІНДЕРДІ ТАЛДАУ НЕГІЗІНДЕ АВТОМАТТЫ МОНИТОРИНГТЕУ ЖҮЙЕСІН ӘЗІРЛЕУ ЖӘНЕ ВАЛИДАЦИЯЛАУ

Жүрек-қантамыр аурулары өлім-жітімнің жетекші себептерінің бірі болып қала береді, бұл кардиологиялық кескіндерді талдаудың тұрақты әдістерін және пациенттерді мониторингтеу жүйелерін әзірлеудің өзектілігін айқындайды. Осы жұмыста ғылыми жоба (IRN: AP05132044) аясында әзірленген биомедициналық кескіндерді автоматтандырылған алдын ала өңдеу және сегментациялау жүйесі ұсынылып, валидтелді. Эксперименттік протокол ашық Heart Database деректер жиыны негізінде (18 пациент, 3D+t МРТ) жүзеге асырылды, бағалау үшін эндокардтың сараптамалық маскалары және 36 кесінді (диастола/систола) пайдаланылды. Бағалау PSNR, SSIM, Dice және IoU метрикалары бойынша жүргізілді. Салыстырмалы талдау алдын ала өңдеудің бес режимін қамтыды: none, Gaussian, wavelet, NLM және hybrid (wavelet + NLM + CLAHE). Нәтижелер NLM әдісінің шу басу сапасы бойынша ең жоғары көрсеткішке ие екенін көрсетті (PSNR = 26,07±0,33 dB, ал baseline үшін 22,85±0,21 dB, $p=1,46\cdot10^{-11}$, Уилкоксон критерийі), ал сегментацияның ең жоғары *дәлдігі hybrid-алдын ала өңдеу кезінде байқалды (Dice = 0,681±0,176, ал алдын ала өңдеусіз 0,636±0,153, p=0,018). «Күрделі жағдайларды» талдау сегментация сапасының эндокард контрастына және жүрек циклі фазаларындағы геометриялық күрделілікке тәуелді екенін көрсетті. Алынған нәтижелер алдын ала өңдеу кезеңінің downstream-сегментация сапасына статистикалық тұрғыдан маңызды әсер ететінін көрсетеді және «алдын ала өңдеу-сегментация-бағалау» кешенді конвейерін клиникалық мониторинг жүйелерін әзірлеудің инженерлік негізі ретінде қолданудың орынды екенін дәлелдейді. Ұсынылған тәсіл нақты деректердің гетерогенділігі жағдайында тұрақты және қайта өндірілуі мүмкін жұмысқа бағытталған және оны клиникалық ақпараттық жүйелерге одан әрі енгізудің негізі ретінде қарастыруға болады.*

Түйін сөздер: *биомедициналық кескіндер, кардиологиялық мониторинг, терең оқыту, жүрек сегментациясы, шу басу, шығару фракциясы, қашықтан денсаулық сақтау.*

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РАЗРАБОТКА И ВАЛИДАЦИЯ СИСТЕМЫ АВТОМАТИЧЕСКОГО МОНИТОРИНГА ПАЦИЕНТОВ С СЕРДЕЧНО-СОСУДИСТЫМИ ЗАБОЛЕВАНИЯМИ НА ОСНОВЕ АНАЛИЗА БИОМЕДИЦИНСКИХ ИЗОБРАЖЕНИЙ

Сердечно-сосудистые заболевания остаются ведущей причиной смертности, что определяет актуальность разработки устойчивых методов анализа кардиологических изображений и систем мониторинга пациентов. В работе представлен и валидирован интегрированный прототип конвейера и сегментации биомедицинских изображений, разработанная в рамках научного проекта (IRN: AP05132044). Экспериментальный протокол реализован на открытом наборе данных Heart Database (18 пациентов, 3D+t МРТ) с использованием экспертных масок эндокарда и 36 срезов (диастола/систола). Оценка качества проводилась по метрикам PSNR, SSIM, Dice и IoU. Сравнительный анализ включал пять режимов предобработки: none, Gaussian, wavelet, NLM и hybrid (wavelet + NLM + CLAHE). Показано, что метод NLM обеспечивает наилучшее качество шумоподавления (PSNR = 26,07±0,33 dB против 22,85±0,21 dB для baseline, $p=1,46\cdot10^{-11}$, критерий Уилкоксона), тогда как максимальная точность сегментации достигается при hybrid-предобработке (Dice = 0,681±0,176 против 0,636±0,153 без предобработки, p=0,018). Проведён анализ «трудных» случаев, выявивший зависимость качества сегментации от контрастности эндокарда и геометрической сложности в различных фазах сердечного цикла. Полученные результаты демонстрируют статистически значимое влияние этапа предобработки на качество downstream-сегментации и подтверждают целесообразность использования комплексного конвейера «предобработка-сегментация-оценка» как инженерной основы для разработки систем клинического мониторинга. Предложенный подход ориентирован на воспроизводимую работу в условиях реальной неоднородности данных и может быть использован в качестве основы для дальнейшей интеграции в клинические информационные системы.

Ключевые слова: *биомедицинские изображения, кардиологический мониторинг, глубокое обучение, сегментация сердца, шумоподавление, фракция выброса, удаленное здравоохранение.*

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АНЫҚТАЛМАҒАН ПАРАМЕТРЛІ ЕКІНШІ РЕТТІ СЫЗЫҚТЫҚ ЕМЕС ЖҮЙЕЛЕРДІ КЕРІ ҚАДАМ ӘДІСІНЕ НЕГІЗДЕЛГЕН АДАПТИВТІ РОБАСТТЫ БАСҚАРУ

Аңдатпа: *Мақалада анықталмаған параметрлі және сыртқы әсері бар сызықтық емес қатаң кері байланыс класс нысанын басқару есебі зерттеледі. Зерттеудің негізгі мақсаты – жүйенің робасттылығын қамтамасыз ететін және барлық сигналдардың кең ауқымды бірқалыпты шектелгендігін қамтамасыз ететін адаптивті басқару алгоритмін әзірлеу.*

Белгісіз динамикалық функцияларды компенсациялау үшін рекурсивті синтез (backstepping) әдісі мен адаптивті аппроксимация заңдары біріктіріліп қолданылды. Тұйықталған жүйенің кең