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Transformer-based automated coronary artery segmentation with domain-specific pretraining

Nouar Ismail¹, Alexandra S. Vatian², Artem D. Beresnev³, Alexey A. Zubanenko⁴, Natalia F. Gusarova⁵✉, Igor A. Men'kov⁶

^{1,2,3,4,5} ITMO University, Saint Petersburg, 197101, Russian Federation

⁴ Imaging Medical Vision LLC, Saint Petersburg, 191119, Russian Federation

⁶ The S.M. Kirov Military Medical Academy, Saint Petersburg, 194044, Russian Federation

¹ noauresmail@gmail.com, <https://orcid.org/0009-0003-3545-9719>

² alexvatyan@gmail.com, <https://orcid.org/0000-0002-5483-716X>

³ artem.beresnev@itmo.ru, <https://orcid.org/0000-0002-4646-6856>

⁴ zubdocmri@gmail.com, <https://orcid.org/0000-0001-6953-5239>

⁵ natfed@list.ru✉, <https://orcid.org/0000-0002-1361-6037>

⁶ i.menkov@gmail.com, <https://orcid.org/0000-0002-1569-2180>

Abstract

Automated segmentation of coronary arteries in coronary computed tomography angiography plays an important role in the diagnosis and treatment of coronary artery disease. Manual segmentation of coronary arteries requires significant labor costs and is accompanied by subjective errors, which necessitates the development of accurate and reliable automated methods for coronary artery segmentation. The paper presents an approach based on a deep neural network with the Swin-UNETR architecture which combines the advantages of visual transformers and the U-Net structure. To improve the accuracy, a domain-specific transfer learning strategy was used: the model was pre-trained on the ImageCAS dataset, and then further trained on a specialized dataset created for Automated Segmentation of Coronary Arteries (ASOCA) Challenge with expert labeling of coronary arteries. The accuracy of the model was assessed on 10 test Computed Tomography Coronary Angiography cases from the ASOCA dataset. The average Dice coefficient was 0.8778, and the average 95th percentile Hausdorff distance (HD_{95}) was 11.66 mm. The obtained results demonstrate that the accuracy of the proposed method is at the level of the leading models presented in the official ASOCA Challenge rating and exceeds the average inter-rater labeling. The proposed method provides high accuracy of coronary artery segmentation. In the future, the introduction of post-processing methods such as connected component filtering or vessel tracking, and spatial attention mechanisms can improve the accuracy of arterial contour localization and the adaptability of the model to various types of computed tomography data.

Keywords

coronary artery, computed tomography coronary angiography (CTCA), deep learning, Swin-UNETR, vision transformers, medical image segmentation, transfer learning, ImageCAS, ASOCA

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Автоматизированная сегментация коронарных артерий на основе трансформера с доменно-специфической предварительной подготовкой

Нуар Исмаил¹, Александра Сергеевна Ватян², Артем Дмитриевич Береснев³,
Алексей Александрович Зубаненко⁴, Наталия Федоровна Гусарова⁵✉,
Игорь Анатольевич Меньков⁶

^{1,2,3,4,5} Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация

⁴ ООО ИМВИЖН, Санкт-Петербург, 191119, Российская Федерация

⁶ Военно-медицинская академия имени С.М. Кирова, Санкт-Петербург, 194044, Российская Федерация

¹ noauresmail@gmail.com, <https://orcid.org/0009-0003-3545-9719>

² alexvatyan@gmail.com, <https://orcid.org/0000-0002-5483-716X>

³ artem.beresnev@itmo.ru, <https://orcid.org/0000-0002-4646-6856>

⁴ zubdocmri@gmail.com, <https://orcid.org/0000-0001-6953-5239>

⁵ natfed@list.ru✉, <https://orcid.org/0000-0002-1361-6037>

⁶ i.menkov@gmail.com, <https://orcid.org/0000-0002-1569-2180>

Аннотация

Введение. Автоматизированная сегментация коронарных артерий при компьютерной томографической коронарографии играет важную роль в диагностике и лечении ишемической болезни сердца. Ручная сегментация коронарных артерий требует значительных трудозатрат и сопровождается субъективными погрешностями, что обуславливает необходимость разработки точных и надежных автоматизированных методов сегментации. **Метод.** В работе представлен подход на основе глубокой нейронной сети с архитектурой Swin-UNETR, сочетающей преимущества визуальных трансформеров и структуры U-Net. Для повышения точности применена доменно-специфическая стратегия трансферного обучения: модель предварительно обучена на наборе данных ImageCAS, после чего дообучена на специализированном — Automated Segmentation of Normal and Diseased Coronary Arteries (ASOCA) с экспертной разметкой коронарных артерий. **Основные результаты.** Оценка точности модели выполнена на 10 тестовых случаях из набора ASOCA. Средний коэффициент Дайса составил 0,8778, а среднее значение 95 % — расстояния Хаусдорфа (HD₉₅) — 11,66 мм. Полученные результаты демонстрируют, что точность предложенного метода находится на уровне ведущих моделей, представленных в официальном рейтинге ASOCA Challenge, и превосходит средний показатель межэкспертной разметки. **Обсуждение.** Предложенный метод обеспечивает высокую точность сегментации коронарных артерий. Вместе с тем отмечена вариабельность результатов по HD₉₅, обусловленная отсутствием специализированной постобработки, чувствительностью к мелким сосудам и различиями в характеристиках тестовых данных. В перспективе внедрение методов постобработки, таких как фильтрация связанных компонентов или отслеживание сосудов, а также механизмов пространственного внимания, может повысить точность локализации артериального контура и адаптируемость модели к различным типам данных компьютерной томографии.

Ключевые слова

коронарные артерии, компьютерная томографическая коронарография с контрастным усилением, глубокое обучение, Swin-UNETR, визуальный трансформер, сегментация медицинских изображений, трансферное обучение, ImageCAS, ASOCA

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Introduction and motivation

Coronary Artery Disease (CAD) is one of the leading causes of death worldwide [1]. It occurs when atherosclerotic plaque builds up in the coronary arteries, causing narrowing or blockage that reduces blood flow to the heart muscle. This condition, known as stenosis, can lead to chest pain (angina), ischemia, or even myocardial infarction if left untreated [2]. Accurate and early detection of coronary stenosis is essential for effective diagnosis and treatment planning.

Coronary Computed Tomography Angiography (CCTA) is increasingly used as a non-invasive method for initial diagnosis. CCTA provides 3D images of coronary arteries and can often help avoid unnecessary invasive procedures. The analysis of the resulting images is increasingly

performed in specialized software packages which can be divided into three groups:

1. Software packages certified for use in clinical practice — Syngo.via (Siemens Healthineers)¹, Vitrea Advanced Visualization (Canon Medical Systems) [3], to name a few;
2. AI-based and cloud-based solutions used as auxiliary tools — HeartFlow FFRct [4], Cleerly [5];
3. Research-oriented or semi-clinical software — 3D Slicer [6] containing vascular modeling toolkit, MITK [7, 8], to name a few.

Resources of groups 1 and 2 are proprietary, i.e. paid, which prevents their use when official localization

¹ Syngo.CT Coronary Analysis (syngo.CT Applications) | Instructions for Use. C2-via-CA.621.07.02.02.

is impossible. In addition, the development of clinical practice creates new needs of clinicians in CCTA analysis, the response to which is an incessant flow of research in this area.

Automated segmentation methods initially relied on traditional approaches, such as Active Shape Models (ASMs), Active Contour Models (ACMs), and atlas-based techniques [9]. The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), revolutionized coronary artery segmentation by enabling automated feature extraction directly from imaging data, significantly improving accuracy and robustness [10]. Models like U-Net, 3D U-Net, and nnU-Net have achieved strong results [11, 12]. Recently, transformer-based models have gained popularity for image segmentation. Several adaptations, including the 3D U-Net, were developed to handle volumetric data, enhancing performance in complex segmentation tasks [13]. Chen et al. [13] proposed a multi-channel 3D U-Net incorporating vesselness maps, improving accuracy by emphasizing tubular structures in Computed Tomography Angiography (CTA) images.

Despite significant advancements, coronary artery segmentation remains challenging due to issues like low contrast, small vessel diameter, and severe class imbalance in imaging data. To address these challenges, specialized loss functions such as focal loss have been employed, as demonstrated by Chen et al. [14] with their 3D Dense-U-Net model which achieved improved segmentation by effectively mitigating class imbalance. Additionally, attention mechanisms and residual connections have been explored to further enhance segmentation accuracy. Wang et al. [15] introduced the DR-LCT-UNet, integrating dense residual modules with local contextual transformers, effectively capturing rich context and achieving superior results compared to traditional 3D U-Net models. Zhang et al. [16] successfully utilized Swin-UNET for medical images segmentation, highlighting its efficiency and accuracy compared to conventional CNN-based models.

Training transformer-based models from scratch requires large datasets. However, models pretrained on large-scale medical imaging datasets capture robust low- and mid-level features — such as edges, textures, and anatomical patterns — which can be effectively adapted to niche tasks like coronary artery segmentation where labeled data are scarce [17, 18]. These pretrained weights not only accelerate convergence by reducing the number of required training epochs but also enhance generalization on the target dataset, mitigating overfitting [19]. In transformer-based architectures like Swin UNETR, pretrained on volumetric CT datasets (e.g., Beyond the Cranial Vault (BTCV), Medical Segmentation Decathlon [20]), transfer learning has shown superior performance in downstream segmentation tasks, outperforming fully convolutional models [21].

The best methods of computed tomography angiography of coronary vessels are accumulated and compared within the Automated Segmentation of Normal and Diseased Coronary Arteries (ASOCA) challenge [22].

For an objective comparison of the proposed technical solutions, the ASOCA Challenge Dataset [23] was developed. It is a large-scale dataset consisting of over

1000 cases from realistic clinical scenarios at Guangdong Provincial People's Hospital from April 2012 to December 2018. This publicly available dataset is significantly larger than previous datasets and is intended as a benchmark for comparing different network architectures. Since 2020, it has become the de facto standard for assessing the effectiveness of emerging developments in the field of CCTA analysis automation. We emphasize that such assessments do not replace clinical trials but are a necessary step in assessing the potential of the proposed technical solution on the way to its clinical certification.

In our study, we aim to create a lightweight, open-source solution of group 3 in the field of research-oriented or semi-clinical software for CCTA segmentation that meets modern requirements for the level of software implementation and accuracy. In our solution, pretrained Swin UNET weights from ImageCAS [24] and BTCV serve as a solid foundation, enabling more efficient and effective fine-tuning on the smaller ASOCA dataset. We utilize the ASOCA dataset to evaluate and benchmark the performance of the proposed segmentation method in comparison with SOTA models presented at ASOCA Challenge.

Research methodology

Scope and Technologies

In our study, we leveraged a modern deep learning pipeline composed of PyTorch, PyTorch Lightning, and MONAI to implement and manage coronary artery segmentation models. PyTorch is a widely adopted, open-source deep learning framework that provides flexibility, high performance through its C++/CUDA backend, and ease of use via Python integration. To streamline training and reduce boilerplate code, we utilized PyTorch Lightning — a lightweight wrapper that structures the code into modular components, such as LightningModule, while handling tasks like GPU management, logging, and checkpointing. For medical imaging-specific needs, we employed Medical Open Network for AI (MONAI), an open-source framework built on PyTorch. MONAI provides domain-tailored tools for medical image processing, including specialized data loaders, transforms, architectures, and evaluation metrics. The framework consists of three core components: MONAI Core, which supports model development and training; MONAI Deploy, which facilitates integration into clinical workflows; and MONAI Label, an AI-assisted annotation tool that integrates with platforms like 3D Slicer to accelerate dataset labeling. This integrated toolchain enabled efficient experimentation and deployment within a medical imaging context.

This study proposes a deep learning-based segmentation framework for extracting coronary arteries from contrast-enhanced CT Coronary Angiography (CTCA) images (Fig. 1). The methodology is structured into four main stages: dataset analysis, transfer learning, fine-tuning, and evaluation. All experiments were conducted on a high-performance workstation equipped with an NVIDIA TITAN RTX GPU featuring 24 GB of VRAM, allowing efficient processing of high-resolution 3D volumes and large batch sizes without memory bottlenecks.

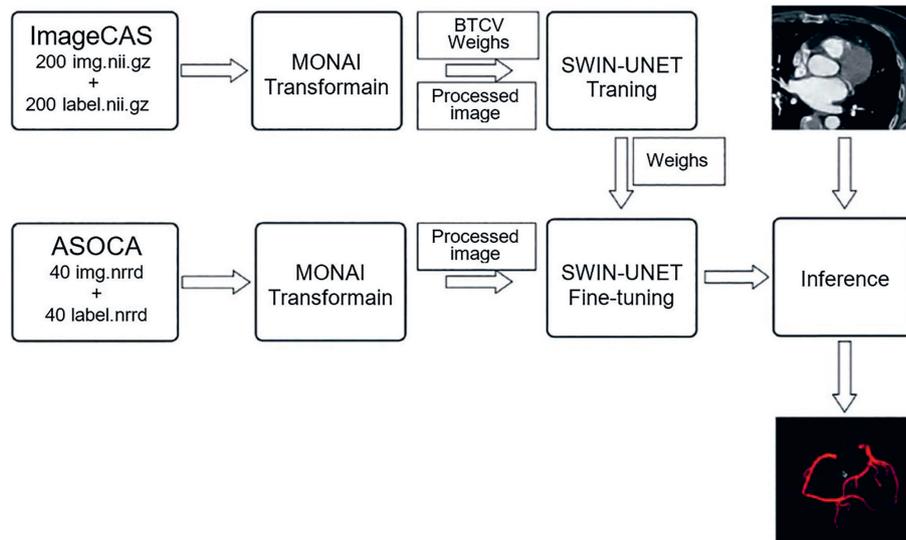


Fig. 1. Overview of the Proposed Coronary Artery Segmentation Pipeline

Data Analysis and Preprocessing

To ensure consistency across datasets and guide transform selection, we conducted an exploratory analysis using the DataAnalyzer class from MONAI Auto3DSeg framework. This tool was used independently on both the ImageCAS and ASOCA datasets to extract voxel spacing, intensity range, and average shape. The analysis gave us insight into our preprocessing pipeline, which includes resampling all volumes to a unified spacing, intensity normalization to the [0, 1] range, channel formatting, and region-of-interest cropping. These transformations were essential to harmonize differences in scanner settings and resolution between datasets.

Model Initialization and Pretraining

For the segmentation backbone, we adopted Swin-UNETR, a transformer-based encoder-decoder model tailored for volumetric medical image segmentation. The encoder consists of hierarchical Swin Transformer blocks which model both short- and long-range dependencies through shifted window attention. The model was first initialized with pretrained weights from the BTCV dataset which provides anatomical diversity through multi-organ labels in abdominal CTs. We then pretrained the model on ImageCAS, a dataset containing over 100 CTCA scans, using a curated subset of 111 cases. This pretraining phase helped the model adapt to coronary artery-specific textures and geometry before exposure to the target dataset. The training process employed the AdamW optimizer with a base learning rate of $2 \cdot 10^{-4}$, a warmup scheduler, and a combined Dice + Focal Loss function to handle class imbalance.

Fine-Tuning on ASOCA

Once the model converged on ImageCAS, it was fine-tuned using the ASOCA Challenge dataset which provides high-quality, expert-annotated coronary artery segmentations. This phase aimed to adapt the pretrained model to the exact imaging protocol and labeling schema used in the ASOCA benchmark. Training was conducted for up to 500 epochs, with early stopping based on validation Dice score. Evaluation was performed every 10 epochs

using a sliding window inference approach and was monitored via TensorBoard logs and quantitative metrics.

Evaluation Metrics. We evaluated the segmentation quality using the Dice Similarity Coefficient (DSC) and the 95th percentile Hausdorff Distance (HD_{95}):

The DSC measures the overlap between predicted and ground truth segmentations. It is defined as:

$$DSC = \frac{2|P \cap G|}{|P| + |G|}$$

Here P is the predicted segmentation; G is the ground truth segmentation; $|P \cap G|$ is the number of overlapping voxels. A Dice score of 1 indicates perfect overlap.

The HD measures the maximum distance from a point on one surface to the nearest point on the other. We use the HD_{95} version to reduce sensitivity to outliers:

$$HD_{95}(P, G) = \max \left\{ \sup_{p \in P} \inf_{g \in G} \|p - g\|, \sup_{g \in G} \inf_{p \in P} \|g - p\| \right\}_{95\%}$$

Here $\|p - g\|$ is the Euclidean distance between boundary points. The subscript 95 % denotes the 95th percentile, which makes the metric more robust to outliers compared to the standard Hausdorff Distance. This metric reflects boundary agreement and penalizes extreme deviations, which is critical in clinical applications like coronary segmentation.

Inference and Post-processing. After training, the best model was used to infer segmentation on the ASOCA test set. Inference predictions were post-processed using thresholding, connected component filtering, and re-orientation transforms to match the original affine metadata. Outputs were saved in NIfTI format and converted to the required structure for ASOCA submission. Additionally, qualitative comparison with expert annotations was visualized in both 2D cross-sectional slices and 3D surface renderings. The pipeline begins with two datasets: ImageCAS, containing 200 CTCA scans in NIfTI format, and ASOCA, comprising 40 scans in NRRD format. Each dataset includes corresponding segmentation labels.

Both datasets undergo preprocessing and augmentation using tailored MONAI transform pipelines. The SwinUNET model is initially pretrained on ImageCAS, using BTCV weights for initialization. After convergence, the best model weights are fine-tuned on the ASOCA dataset to adapt to its specific annotation style and imaging characteristics.

The fine-tuned model is then used to perform inference on unseen ASOCA images. Finally, 2D slices and 3D reconstructions are generated to qualitatively evaluate segmentation performance and visualize anatomical accuracy.

Results and Comparative Analysis

An example of images segmented by our method, in comparison with manual segmentation and ground truth, is shown in Fig. 2.

Our results are presented in Table 1. For comparison, Table 2 shows the best results from the ASOCA Challenge.

To evaluate the performance of our proposed SwinUNET-based segmentation pipeline, we tested the model on 10 representative CTCA cases from the ASOCA dataset. As shown in Table 1, the model achieved a mean DSC of 0.8778 and an average Hausdorff Distance (HD_{95}) of 11.656 mm across all cases. Notably, the Dice scores remained consistently high, with several cases, such as Case 6 (0.9340), Case 8 (0.9253), and Case 9 (0.8959), demonstrating very close agreement with expert annotations. Meanwhile, low HD_{95} values in Case 6 through Case 9 (all ≤ 1.00 mm) suggest precise boundary localization in many test cases.

Table 1. Dice Score and 95th percentile Hausdorff Distance (HD_{95}) for proposed model

Case No.	Dice Score	HD_{95} , mm
1	0.8573	34.76
2	0.8700	1.41
3	0.8637	4.12
4	0.8442	22.47
5	0.9340	21.02
6	0.8540	1.00
7	0.9253	1.00
8	0.8573	1.00
9	0.8959	1.00
10	0.8342	24.78
Mean	0.8778	11.66

When comparing these results to the official ASOCA Challenge leaderboard (Table 2), our model average Dice score of 0.8778 is competitive with top-performing methods such as “Submission 1” (0.87 ± 0.04) and the “Top 7 Ensemble” (0.87 ± 0.04). While ensemble methods show slightly lower HD values (e.g., 1.56 (SD:2.55) mm), our model Dice scores fall well within the top five single-model submissions, as shown in the leaderboard. In particular, our results exceed those of Submission 5 to Submission 8, and are on par with or slightly above Submission 2 and Submission 4 in segmentation accuracy.

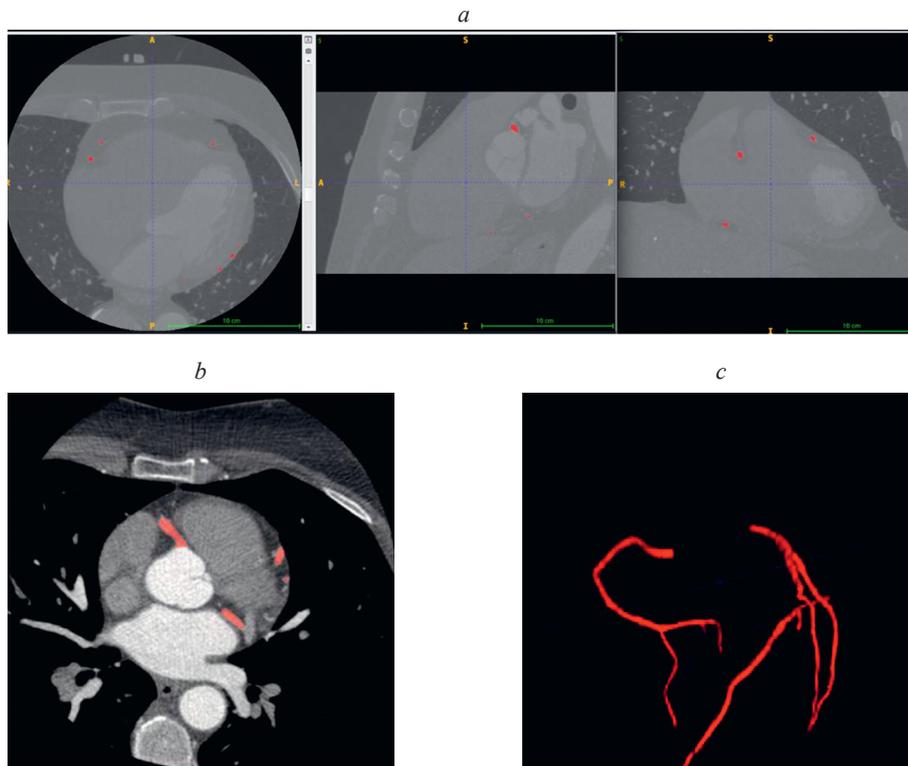


Fig. 2. Example of Coronary Artery Segmentation: manual segmentation in three planes using specialized software (a); ground truth method (b); predicted segmentation (3D reconstruction) (c)

Table 2. Summary of Dice Score and Hausdorff Distance for each method (official results from ASOCA Challenge)

Submission	Dice Score	HD ₉₅ , mm (mean ±SD)
Top 3 Ensemble	0.88 ± 0.04	1.56 (SD:2.55)
Top 5 Ensemble	0.88 ± 0.04	1.73 (SD:2.08)
Top 6 Ensemble	0.87 ± 0.04	1.61 (SD:2.17)
Submission 1	0.87 ± 0.04	4.16 (SD:7.13)
Submission 2	0.84 ± 0.05	2.34 (SD:2.92)
Submission 3	0.86 ± 0.07	6.22 (SD:15.52)
Submission 4	0.87 ± 0.05	6.57 (SD:14.27)
Submission 5	0.80 ± 0.04	3.31 (SD:3.42)
Submission 6	0.84 ± 0.06	7.73 (SD:11.83)
Submission 7	0.78 ± 0.10	4.77 (SD:3.51)
Submission 8	0.73 ± 0.05	6.55 (SD:7.40)

Note: Data from from [23, Table 1]. (SD: ...) represents the standard deviation across 20 test cases. High SD values for HD₉₅ reflect variability due to anatomical features and artifacts; negative values when subtracting SD are not realistic, as HD₉₅ ≥ 0 mm.

However, our Hausdorff Distances show greater variance, with high values in certain cases (e.g., Case 1: 34.76 mm, Case 10: 24.78 mm), likely due to minor discontinuities or spurious predictions in elongated artery branches. These outliers suggest that post-processing techniques, such as connected component filtering or vessel tracking, could further enhance the robustness of boundary accuracy without sacrificing overall Dice performance.

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To summarize, despite not being an ensemble approach, our model achieves performance comparable to several of the top single-system entries on the ASOCA leaderboard. This affirms that the Swin-UNET with transfer learning from BTCV and ImageCAS is a strong standalone model and may serve as a reliable reference architecture for coronary artery segmentation in future research.

Conclusion

In this study, we presented a deep learning-based pipeline for coronary artery segmentation in Computed Tomography Coronary Angiography images, leveraging the Swin-UNETR architecture and domain-specific transfer learning. By pretraining the model on the ImageCAS dataset and fine-tuning it on the Automated Segmentation of Coronary Arteries Challenge (ASOCA) Challenge dataset, we achieved a mean Dice score of 0.8778 across 10 test cases — results that are competitive with top-performing entries in the ASOCA benchmark. The effectiveness of our approach highlights the importance of using anatomically relevant pretraining data and transformer-based architectures for vascular segmentation tasks. While our model performed strongly overall, some variability in boundary localization suggests that incorporating post-processing techniques or spatial attention mechanisms could further enhance segmentation robustness. Overall, our pipeline provides a reliable and efficient solution for automated coronary artery segmentation and can serve as a reference framework for future research applications.

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Authors

Noaur Ismail — PhD Student, ITMO University, Saint Petersburg, 197101, Russian Federation, <https://orcid.org/0009-0003-3545-9719>, noauresmail@gmail.com

Alexandra S. Vatian — PhD, Dean, ITMO University, Saint Petersburg, 197101, Russian Federation, [sc 57191870868](https://orcid.org/0000-0002-5483-716X), <https://orcid.org/0000-0002-5483-716X>, alexvatyan@gmail.com

Artem D. Beresnev — PhD, Vice Dean, ITMO University, Saint Petersburg, 197101, Russian Federation, [sc 57202210221](https://orcid.org/0000-0002-4646-6856), <https://orcid.org/0000-0002-4646-6856>, artem.beresnev@itmo.ru

Alexey A. Zubanenko — CEO, Imaging Medical Vision LLC, Saint Petersburg, 191119, Russian Federation; PhD Student, ITMO University, Saint Petersburg, 197101, Russian Federation, [sc 57215436184](https://orcid.org/0000-0001-6953-5239), <https://orcid.org/0000-0001-6953-5239>, zubdocmri@gmail.com

Natalia F. Gusarova — PhD, Senior Researcher, Associate Professor, ITMO University, Saint Petersburg, 197101, Russian Federation, [sc 57162764200](https://orcid.org/0000-0002-1361-6037), <https://orcid.org/0000-0002-1361-6037>, natfed@list.ru

Igor A. Men'kov — PhD (Medicine), Head of Department, The S.M. Kirov Military Medical Academy, Saint Petersburg, 194044, Russian Federation, <https://orcid.org/0000-0002-1569-2180>, i.menkov@gmail.com

Авторы

Исмаил Нуар — аспирант, Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация, <https://orcid.org/0009-0003-3545-9719>, noauresmail@gmail.com

Ватьян Александра Сергеевна — кандидат технических наук, декан, Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация, [sc 57191870868](https://orcid.org/0000-0002-5483-716X), <https://orcid.org/0000-0002-5483-716X>, alexvatyan@gmail.com

Береснев Артем Дмитриевич — кандидат технических наук, заместитель декана, Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация, [sc 57202210221](https://orcid.org/0000-0002-4646-6856), <https://orcid.org/0000-0002-4646-6856>, artem.beresnev@itmo.ru

Зубаненко Алексей Александрович — генеральный директор, ООО ИМВИЖН, Санкт-Петербург, 191119, Российская Федерация; аспирант, Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация, [sc 57215436184](https://orcid.org/0000-0001-6953-5239), <https://orcid.org/0000-0001-6953-5239>, zubdocmri@gmail.com

Гусарова Наталия Федоровна — кандидат технических наук, старший научный сотрудник, доцент, Университет ИТМО, Санкт-Петербург, 197101, Российская Федерация, [sc 57162764200](https://orcid.org/0000-0002-1361-6037), <https://orcid.org/0000-0002-1361-6037>, natfed@list.ru

Меньков Игорь Анатольевич — кандидат медицинских наук, заведующий отделением, Военно-медицинская академия имени С.М. Кирова, Санкт-Петербург, 194044, Российская Федерация, <https://orcid.org/0000-0002-1569-2180>, i.menkov@gmail.com

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