ARTIFICIAL INTELLIGENCE ALGORITHMS FOR ASSESSMENT OF THE MAJOR VESSEL TORTUOSITY

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Tortuosity of the coronary, cerebral arteries, aorta and its branches remains an important vascular problem, which, on the one hand, complicates selection of the X-ray surgical treatment tactics, and on the other hand worsens the disease outcome. The lack of common standards for assessment of tortuosity of the coronary, cerebral arteries, aorta and its branches reduces the diagnosis accuracy in patients at high risk of cardiovascular events. The use of machine learning for automated tortuosity assessment represents one possible solution to this problem. The study aimed to analyze and compare accuracy, feasibility, and limitations of the available methods for automated assessment of tortuosity of the coronary, cerebral arteries, aorta and its branches using the machine learning tools. The systematic review was conducted in accordance with the PRISMA protocol. The search for papers published in 2015–2025 in the PubMed, Scopus, and eLibrary databases was performed using the following keywords: deep learning, machine learning, artificial intelligence, vessel tortuosity, curvature. Six papers out of 240 were included in the analysis. The analysis has shown that 80% of approaches are based on convolutional neural networks, and skeletonization aimed to isolate small blood vessels from the artery represents an essential preprocessing phase. In 50% of papers, tortuosity was determined qualitatively based on the presence of bending angles over 45°. Quantitatively, tortuosity was determined as a distance coefficient and a measure of curvature. In three studies out of six, verification of estimates was carried out by comparing the results with expert opinions (accuracy was 0.92–0.94). The study limitations are as follows: monocentricity, the use of data from one type of equipment.

Keywords: vessel tortuosity, coronary arteries, cerebral arteries, aorta and its branches, machine learning, artificial intelligence, tortuousity index

Author contribution: Ilina AA, Bikmeyev AT — search for papers, manuscript writing; Lakman IA — study design, data processing, manuscript writing and editing; Enikeeva AR, Badykova EA — experts in manual selection of papers, Zagidullin NSh — expert in manual selection of papers, manuscript writing and editing; Bryukhanova OA — manuscript editing.

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Received: 22.12.2025 **Accepted:** 26.01.2026 **Published online:** 05.02.2026

DOI: 10.24075/brsmu.2026.005

АЛГОРИТМЫ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ ОЦЕНКИ ИЗВИТОСТИ МАГИСТРАЛЬНЫХ СОСУДОВ

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Извитость коронарных, цереброваскулярных артерий, аорты и ее ветвей остается одной из значимых сосудистых проблем, которая с одной стороны осложняет выбор тактики рентгенохирургического лечения, а с другой — ухудшает прогноз самого заболевания. Отсутствие единых стандартов оценки извитости коронарных, цереброваскулярных артерий, аорты и ее ветвей снижает точность диагностики пациентов с высоким риском сердечно-сосудистых событий. Одним из возможных решений данной проблемы является применение машинного обучения для автоматической оценки извитости. Целью исследования было провести анализ и сравнение точности, клинической применимости и ограничений существующих методов автоматической оценки извитости коронарных, цереброваскулярных артерий, аорты и ее ветвей с использованием инструментов машинного обучения. Систематический обзор проводили по протоколу PRISMA с поиском статей в базах данных PubMed, Scopus и eLibrary за период с 2015 по 2025 гг. по ключевым словам: deep learning, machine learning, artificial intelligence, vessel tortuosity, curvature. Из 240 выявленных публикаций в анализ было включено шесть. Анализ показал, что 80% подходов основаны на сверточных нейронных сетях, обязательным этапом предобработки изображений является скелетирование для отсечения мелких сосудов от артерии. В 50% статей извитость артерий определяется качественно по наличию углов изгибов более 45°. Количественно извитость определяли как коэффициент расстояния и мера кривизны. Верификацию оценок в трех из шести исследований проводили при сравнении результатов с мнениями экспертов (точность составила 0,92–0,94). Ограничения исследования — моноцентричность, использование данных одного типа оборудования.

Ключевые слова: извитость сосудов, коронарные артерии, цереброваскулярные артерии, аорта и ее ветви, машинное обучение, искусственный интеллект, количественная мера оценки извитости

Вклад авторов: А. А. Ильина, А. Т. Бикмеев — поиск источников, написание статьи; И. А. Лакман — дизайн исследования, обработка данных, написание и редактирование статьи; А. Р. Еникеева, Е. А. Бадыкова — эксперты ручного отбора публикаций, Н. Ш. Загидуллин — эксперт ручного отбора публикаций, написание и редактирование статьи, О. А. Брюханова — редактирование статьи.

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Статья получена: 22.12.2025 **Статья принята к печати:** 26.01.2026 **Опубликована онлайн:** 05.02.2026

DOI: 10.24075/vrgmu.2026.005

High arterial tortuosity induces arterial dysfunction due to a number of reasons: first, tortuous arteries can create turbulent and slow blood flow, leading to decreased efficiency of blood supply to tissues and organs [1]; second, increased stress on the vessel wall may occur due to uneven pressure distribution in the vessel, ultimately leading to endothelial damage [2]; third, difficulties arise with diagnostics (for example, when using angiography) and vascular surgery [3]. Furthermore, standard imaging methods and arterial tortuosity assessment based on these methods are a matter of debate [4].

Cardiovascular disorders associated with the coronary artery abnormalities remain one of the leading causes of premature death all over the world [5]. Radiology plays a key role in detection of those; coronary angiography is acknowledged as a gold standard due to high vascular structure imaging accuracy [6]. The available diagnostic methods usually do not focus on assessing the coronary artery tortuosity, despite possible relationship between tortuosity and adverse outcomes, such as ischemia, spontaneous blood vessel dissection, and complications associated with stent placement [7].

The lack of the common standard of arterial tortuosity assessment and severity limits the diagnostic accuracy [8]. Theoretically, machine learning algorithms, in particular machine vision algorithms, which are widely used in X-ray image recognition tasks, could help solve the problem [9]. However, there are many challenges to training intelligent algorithms in practice. Thus, the coronary angiography technical specifics, including the use of the limited number of standard views, do not allow one to obtain an integrated picture of the vascular bed anatomy. Imaging is also hampered by the overlap of vessels, their shadows, the presence of small branches and bone structures that obscure the image. Further complexities arise from the artifacts associated with the patient's heart movement and breathing, as well as from inconsistent rate and uneven filling of blood vessels with the contrast agent [10]. Therefore, there is a need to summarize the available research allowing for further evaluation of the potential of approaches capable of improving the assessment of arterial tortuosity, specifically tortuosity of the coronary arteries of the heart.

The study aimed to analyze and compare accuracy, feasibility, and limitations of the available methods for assessment of tortuosity of the coronary, cerebral arteries, aorta and its branches using machine learning tools.

METHODS

To answer the research question ("How to automatically determine the presence and degree of arterial tortuosity based on medical images?") the PRISMA protocol was used that is conventionally used for systematic reviews. The search criterion was as follows: studies published not earlier than in 2015 and focused on the intelligent algorithms, methods, and techniques used to assess vascular tortuosity. The earlier studies were not considered due to the fact that the reported technologies were dated. The access to the paper full text was an essential selection criterion. PubMed, Scopus, eLibrary were the databases, in which the search for the review sources was performed. The keywords for the search query in English were as follows: deep learning, machine learning, artificial intelligence, computer vision, coronary, cerebral, carotid, aorta, vessel, artery, tortuosity, curvature. Accordingly, the following keywords in Russian were used: извитость, сосуд, артерия, машинное обучение, компьютерное зрение, искусственный интеллект. The search queries were generated using the OR and AND logical operators for disjunction and conjunction of the terms. The search for papers in the PubMed and Scopus databases was accomplished using appropriate R libraries: pubmedR and rscopus (it was possible, since the authors previously registered in citation databases and got access via API). The "snowball" strategy was used for a broader search for papers in accordance with the research question: we found the necessary paper and conducted further search for the cited and citing sources. Inclusion criteria for the second paper selection phase: presence of characteristics of vascular tortuosity assessment algorithms, methods, and techniques, including information about their accuracy and feasibility. If the article mentioned image preprocessing and processing steps, these were also included in the analysis. Exclusion criteria: discrepancy to the review subject (for example, tortuosity of umbilical vessels). The study limitations and funding were not taken into account when selecting papers. Compliance of each paper with the inclusion criteria was assessed by two independent experts when performing manual selection of papers. In case of disagreement in their opinion regarding any paper, a verification expert was involved. The concurrence of opinions from experts was determined based on the Cronbach's alpha.

Criteria for inclusion of papers in the systematic review: fact of containing the description and/or name of the tortuosity assessment method/technique (TAM-T); fact of containing the description of the TAM-T results; fact of considering arteries only; analysis of blood vessels in adult patients with the mature vascular system (over the age of 18) only; fact of considering images of blood vessels obtained by coronary angiography (CAG), computed tomography (CT) or optical coherence tomography (OCT).

Exclusion criteria: no TAM-T results; description of the study of umbilical vein and/or vessel tortuosity; description of the study of blood vessels in patients under the age of 18; description of the animal study or study involving models, such as computer simulation and microfluid devices.

The sources selected were analyzed with regard to the following: what types of images were used to determine arterial tortuosity; what number of images was used to train machine learning algorithms; what machine learning algorithm was used to recognize images of blood vessels; how blood vessel images were pre-processed; how the arterial tortuosity was quantified; quality metrics for tortuosity assessment.

RESULTS

Primary search in accordance with the specified strategy of combining keywords allowed us to find 240 papers in three databases. In this phase of paper selection, 82 duplicate studies were filtered out, and four papers were not selected due to other reasons (lack of available full-text versions). The remaining publications were re-screened for paper titles and abstracts that matched the answer to the research question, which allowed us to filter out another 69 studies. Full-text versions of the papers selected were analyzed when manually selected by experts, and only one paper was a matter of debate (Cronbach's alpha 0.96). Eventually, among full-test versions selected only six answered the research question, so six papers were selected to analyze and compare the vascular tortuosity assessment algorithms, methods, and techniques. The Figure presents the scheme of paper selection in accordance with the PRISMA protocol.

Convolutional neural networks were used as an arterial tortuosity modeling tool in five papers out of six selected. Thus, two convolutional neural network models (CNN and nnU-Net)

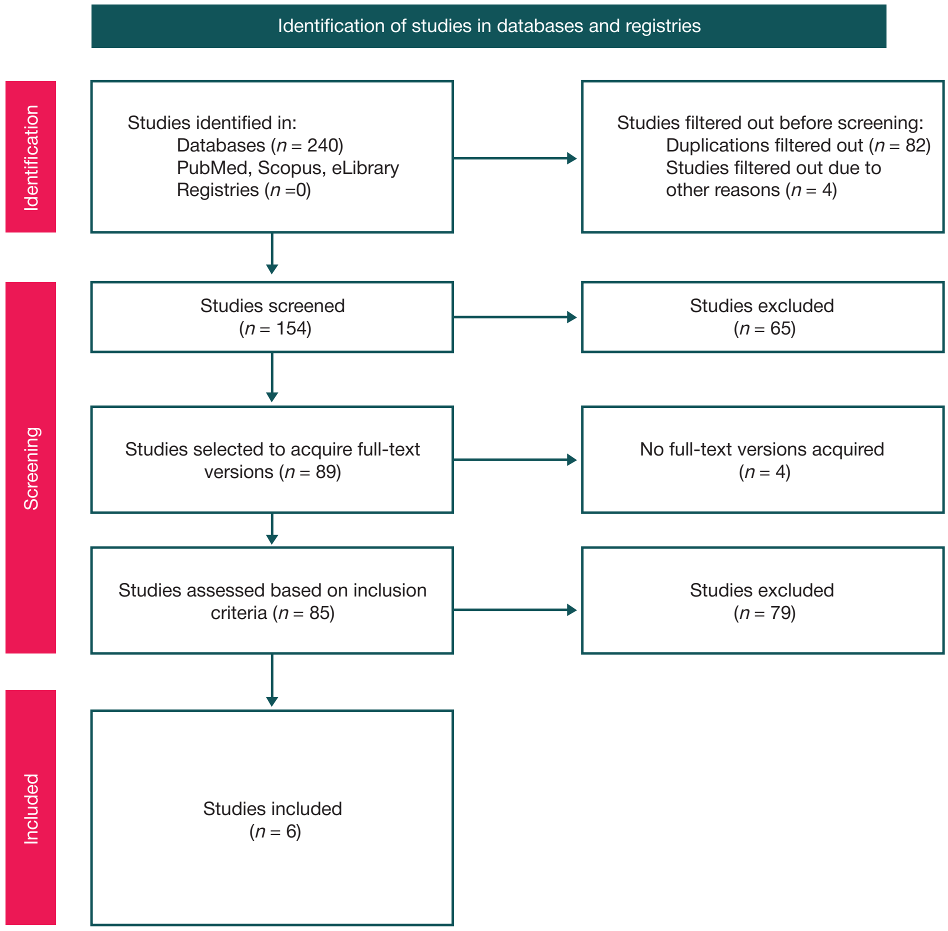

Fig. PRISMA paper selection scheme for the study

for automatic segmentation of coronary arteries and quantitative assessment of their morphological characteristics, including vascular tortuosity, were trained in 2024 [11]. This study involved the analysis of CT angiography images of 281 patients. The input information pre-processing included thresholding with the threshold for selection of blood vessel lumen tailored by an expert (radiologist). Manual adjustment was performed in the over-segmented and under-segmented regions of blood vessel images. Blood vessels were segmented manually using the 3D Slicer free open source software for medical imaging, then the automatic centerline extraction was performed (the so-called vessel skeletonization) using the VMTK (Vascular Modeling Toolkit) library integrated in the 3D Slicer, and the major morphological characteristics of the vessel were calculated. Several approaches were used to assess arterial tortuosity. Global tortuosity was defined as the ratio of the actual blood vessel path length to the direct distance between its ends. Local tortuosity was assessed along the centerline at each point using the 1 cm-long support arcs centered at the point considered. In addition, the tortuosity angle was calculated as arccosine of the scalar product of vectors approximating the blood vessel arc ascending and descending sections by the least squares method. The resulting tortuosity index of blood vessels assessed was determined for each patient as a number of vascular branches having at least three bends with the angle ≥ 45°. In this study, a convolutional neural network (CNN) was trained for automatic blood vessel segmentation, and morphological characteristics were assessed using the nnU-Net neural network-based two-stage cascade approach [11]. At the first stage the multi-view 2.5D U-Net was created. For that three 2D models were trained using the images sliced in orthogonal directions (sagittal, coronal, and axial). Such an approach to vascular tortuosity assessment is particularly useful, since tortuosity can be found in only one view, while in another view it is not always noticeable. At the second stage the data obtained were combined with the original image and used to train the 3D U-Net network. It is noteworthy that the authors assessed the strength of their findings, for that they compared the results of the multi-view 2.5D model and the cascade 3D model. As a result, the value of the Dice coefficient averaged across all patient blood vessel images, as a measure of the quality of image recognition accuracy, increased from 0.791 [0.60; 0.88] to 0.895 [0.75; 0.92]. The fact that all the images used for training were obtained at the same center with the same CT scanner can be noted as a drawback. The use of data from different sources, including open sources, including images of blood vessels of healthy volunteers, might improve stability of the tortuosity assessment model.

In 2023, an automatic segmentation, labeling, and arterial tortuosity assessment method based on artificial neural networks was proposed [12]. To train models, the authors formed a dataset of 566 CT angiography scans from acute ischemic stroke patients, among which 165 images were randomly selected. The pre-processing phase included spatial alignment and intensity normalization. The experts performed segmentation manually, as in the previous solution, in 3D Slicer. The authors tested three segmentation model variants (based on the nnU-Net, UNETR, SwinUNETR neural network models), and nnU-Net turned out to be the most effective (the Dice coefficient was 0.93 ± 0.02). Training involved data augmentation and five-fold cross-validation (additional cross-verification). Next, like in the study [11], the surface model of

Table. Characteristics of the studies included in the systematic review

Authors, year of the study, reference	Type of images analyzed	Image pre-processing methods	Image processing methods	Machine learning method	Sample characteristics	Vessel tortuosity assessment method	Model quality metrics
Nannini G. et al., 2024 [11]	CT angiography	Thresholding with manual selection of the cut-off value	Manual blood vessel segmentation (3D Slicer), centerline extraction	CNN, U-Net	281 patients	≥ 3 bends > 45°, distance coefficient	Dice coefficient: 0.895
Canals P. et al., 2023 [12]	CT angiography	Spatial alignment, color intensity normalization	Manual blood vessel segmentation (3D Slicer), anatomical landmarks, centerlines, calculation of morphological and geometric characteristics	nnU-Net, gU-Net	566 stroke patients	Blood vessel diameter and length, angles of deflection	No
Cobo M. et al., 2023 [13]	Coronary angiography	Cropping	No	Convolutional neural network (Xception)	401 patients , 658 images	≥ 3 bends with the angle ≥ 45°	Accuracy: 0.87, sensitivity 0.87, specificity 0.88
Nageler G. et al., 2023 [14]	CT angiography	No	Segmentation	nnU-Net, 3D CNN	379 post EVT due to acute ischemic stroke	< 90 acute, > 90 obtuse	AUC: 0.92
Gao H. et al., 2022 [15]	3DRA angiography	Segmentation involving the use of thresholding, smoothing, removal of disconnected branches, aneurysm removal	Calculation of geometric characteristics	Logistic regression, ENT, SVM, XGBoost, Random Forest	226 patients post DSA	Curvature, torsion, distance coefficient	Best AUC — 0.762 (SVM)
Witherford M. et al., 2022 [16]	CT angiography	No	Creation of a 3D model of blood vessels	–	234 patients with aortic aneurysm	Distance coefficient	–

blood vessels was extracted from the binary image map using the VMTK library, then filtering and smoothing were applied. A total of 24 characteristics were calculated for each node based on the centerlines obtained, including radii (mean, proximal, distal, minimum and maximum), proximal to distal radius ratio, relative segment length, directions (total and initial), number of points per segment, segment's center of mass coordinates. The authors formed a graph of blood vessel centerlines, the nodes of which denoted vascular segments with the artery names specified. Segments were classified using the graph U-Net neural network after normalization of characteristics and increasing the graph connectivity. The researchers identified and analyzed 33 geometric and morphological characteristics of vascular tortuosity. These included blood vessel diameter, relative segment length, and absolute and relative deflection angles for the major arteries (aorta, brachiocephalic trunk, common carotid and subclavian arteries). Morphological characteristics included the aorta type and the presence of the bovine aortic arch variant. The authors did not calculate a unified tortuosity coefficient, but performed comparative analysis of tortuosity parameters in various groups of patients. They developed an algorithm allowing them to identify the abnormally tortuous blood vessels. All the data used were obtained from the same medical center and one CT equipment manufacturer, which limited generalizability of the results and the method versatility. The automatic analysis sometimes made serious mistakes when determining the key points, which reduced measurement reliability compared to the manual approach. The main sources of error were related to improper blood vessel labeling, segmentation inaccuracy, erroneous centerline extraction and data processing, which affect the overall method accuracy. However, blind validation yielded the recognition accuracy of 0.94.

In 2023, the authors of another paper also used a convolutional neural network, but they proposed an alternative approach to vascular tortuosity assessment that was different from the conventional sequence of actions algorithm [13]. The method to directly classify angiography scans based on the use of convolutional neural networks (CNN) determining the presence or absence of vascular tortuosity was developed. The source material was the dataset of 658 coronary angiography images obtained from 401 patients. To expand the sample, two views were used: Spider (in the form of images taken at a random angle forming a “web”) and 45°. Due to the limited amount of data, the image augmentation technology was used (scaling, shifting and changing the brightness of images). As a result, the authors defined tortuosity as the presence of three or more successive bends with the angle ≥ 45° in any part of the coronary artery. Images were segmented with the Xception convolutional neural network using early stopping in order to avoid retraining of the image recognition algorithm. The so-called transfer learning was used to optimize the algorithm training task, the essence of which was as follows: in the neural network model pre-trained on ImageNet, the last fully connected layer was replaced with the one adapted for the binary classification task. Such an approach made it possible to preserve universal features from ImageNet and adapt these to the medical image specifics. Standard parameters were calculated to estimate the proposed model quality: accuracy (0.87), sensitivity (0.87), specificity (0.88). The main limitations of the method proposed are associated with the image quality and resolution, insufficient variety of images showing different vascular tortuosity types.

In the same year, the automatic method for classifying the internal carotid artery based on the bending angle value was developed [14]. A total of 379 CT angiography scans were used to train algorithms. To expand the sample, both left and right internal carotid arteries of each patient were included in the analysis. As in the above studies, segmentation was performed manually with 3D Slicer using three tags: aorta, left common carotid artery (CCA) + internal carotid artery (ICA), right CCA + ICA. To automate the process of artery segmentation, a neural network with the nnU-Net architecture was trained. Then the hybrid segmentation involving the use of automated prediction with manual verification and adjustment was applied.

The 3D Slicer angle tool was used to measure the ICA bending angles allowing for more accurate consideration of spatial arrangement of individual blood vessels. Angles were classified as acute (≤ 90°) or obtuse (> 90°) depending on their effect on the endovascular intervention duration (angles ≤ 90° turned out to be associated with longer endovascular interventions).

At the image pre-processing stage the following was performed to train the model: cropping of the volume based on segmentation, distinction between the left and right ICA, voxel size unification (0.5 mm), extending the volume size to 400 × × 400 × 605 voxels, and rescaling (a procedure that adds pixels and performs smoothing) to 128 × 128 × 196. The CCA + ICA was the network input, and the binary class (angle > 90° or angle ≤ 90°) was the output. Based on the testing results, the model constructed by the authors showed the AUC classifier evaluation metrics (area under the ROC curve) of 0.92. The major study limitations include the monocentric design, lack of external data validation, planar measurement of angles on 3D segmentations, and loss of information when dichotomizing angles. Furthermore, it was impossible to assess some ICA segments due to insufficient contrast enhancement, which could result in bias of results.

In another study (2022), comparative analysis of the applicability of several machine learning algorithms for the internal carotid artery tortuosity assessment was performed [15]. The analysis included 3DRA angiography scans of 62 patients. At the pre-processing stage, segmentation, smoothing, and removal of the unconnected blood vessel branches were performed using Mimics and Geomagic Studio, then the VMTK library was used for aneurism removal to construct the maternal artery model. Centerlines were calculated in Aneufuse, and the following characteristics were used for tortuosity assessment: curvature, torsion, and the distance coefficient calculated as the ratio of the direct distance between the segment starting and ending points to the centerline length. The average, maximum and range curvature and torsion values were calculated. As a result, the machine learning model for predicting the in-stent stenosis was constructed based on 75 clinical, structural, and morphological variables. The model was trained using logistic regression and four machine learning algorithms: Elastic Net neural network, Support Vector Machines, extreme Gradient Boosting, and Random Forest. When performing test validation, the Support Vector Machines (SVM) algorithm had the best parameters of the AUC-ROC metrics (SVM): 0.891 (test set) and 0.762 (validation set). Among tortuosity parameters, the length coefficient and maximum curvature affected the prognosis most. The key drawbacks of the study, i.e. small sample size (62 patients) and the retrospective single-center design, lowered generalizability of the data obtained. The tortuosity analysis was performed at a global level, without taking into account local blood vessel characteristics, which could affect the accuracy of assessing the relationship with treatment outcomes.

In 2022, the analysis of preoperative anatomy and intraoperative arterial deformities in patients with aortic aneurysms was also conducted [16]. Multiplanar reconstruction with subsequent construction of the 3D blood vessel model was performed in 234 patients. Models were constructed using the CYDAR proprietary software based on preoperative CT scans, where branches of the major arteries were marked (celiac trunk, superior mesenteric, renal and iliac ones). These models were used to create interactive maps during surgery, which allowed for adjustment of anatomical marker positions in three planes in the real-time mode. To assess vascular tortuosity, the tortuosity coefficients were calculated as a ratio of the direct distance to Euclidean distance for the key segments: visceral region (from the celiac trunk to the inferior renal artery), common iliac arteries, and the entire iliac segment. When conducting research, the authors adhered to the standards of the Society for Vascular Surgery in terms of measurement standardization.

The table providing the main characteristics of the arterial tortuosity assessment methods and algorithms was created to summarize the analysis results.

DISCUSSION

The systematic review conducted allowed us to identify six published studies answering the research question ("How to automatically determine the presence and degree of arterial tortuosity based on medical images?"). All the studies were novel, these were published in 2022–2024. The authors of three papers out of six examined tortuosity of the internal carotid artery and supraaortic vessels, in one study — the aorta; in two studies, tortuosity of the coronary arteries was assessed. In five studies out of six, neural networks were used as the main machine learning algorithm; in 50% of papers, 3D Slicer, the freely distributed software for analyzing medical (primarily X-ray) images, was used as a pre-processing tool. In all papers, skeletonization was accomplished at the preliminary stage of the blood vessel image analysis, which was especially important for recognizing and separating the main blood vessels from branches of small vessels, and in three of the six studies, the open source library VMTK was used for this purpose. In three studies out of six, verification was performed when comparing the results with the expert opinions.

As for the answer to the research question, only three papers considered the use of the exact number in the form of the distance coefficient for vascular tortuosity quantification. Furthermore, in one paper, the curvature coefficient (through the second derivative of the approximated function describing the vessel) was also calculated, along with torsion. In three other papers, tortuosity of blood vessels was qualitatively assessed. Any quantification allows one to assess the vessel tortuosity degree, but automatic assessment of the presence of tortuosity itself as a fact of the presence of abnormality is also important. Thus, it has been shown that the presence of coronary artery tortuosity is associated with the early arterial hypertension manifestation [17]. Furthermore, automatic assessment of the presence of vascular tortuosity is important for planning, monitoring and evaluation of the consequences of surgical intervention for stenting. For example, in 2021 the effect of vascular tortuosity on clinical sequelae after stent placement was studied, and conclusions were made that stent implantation in tortuous coronary arteries in pregnancy was associated with the increased rate of coronary artery thrombosis based on the aggregated data of six studied [18]. The paper by other researchers (2021) provides the research results proving that the presence of coronary tortuosity is associated with hypertension, hyperlipidemia, and left ventricular diastolic dysfunction (it is noteworthy that in this study tortuosity was defined as the presence of ≥ 3 bends at an angle greater than 45°) [19]. At the same time, the tortuosity degree quantification allows one to assess the relationship between tortuosity and coronary blood flow alteration, which can cause the decrease in perfusion pressure and, as a consequence, lead to myocardial ischemia [20]. It is noteworthy that the qualitative and quantitative approaches to tortuosity assessment were compared in terms of their effects on the development of coronary artery disease (CAD) [21]. The authors determined tortuosity qualitatively based on angle measurement. They showed that patients with the coronary artery tortuosity were more common in the group of patients with nonobstructive CAD. The authors quantified tortuosity by determining the tortuosity index, based on which they showed that the highest coronary artery tortuosity index values were reported in patients with ischemia of the lateral wall supplied by the left circumflex artery. It was concluded that both qualitative and quantitative coronary blood vessel tortuosity assessment was important for detection of the coronary artery disease predictors. The study conducted in 2023 showed that cerebrovascular tortuosity also affects plaque formation in the carotid bulb [21]. Furthermore, there are data (2024) that tortuosity is a risk factor of the cervicocerebral artery dissection representing the cause of ischemic stroke in the young [22], which once more emphasizes the need for automatic arterial tortuosity assessment with the use of AI tools.

The use of arterial tortuosity quantitative assessment models in clinical practice is associated primarily with the possibility of its seamless integration into clinical scales for stratifying the risk of vascular surgery complications, as well as implementation in the form of separate modules and a system for supporting medical decision-making. For example, SYNTAX Score and SYNTAX Score II consider arterial tortuosity, and according to the papers by domestic authors, these scores are significantly correlated to clinical outcomes in patients with severe coronary artery lesions post percutaneous coronary interventions. In 2019 it was shown that the higher coronary bed structural complexity reflected by the SYNTAX Score was associated with the worse outcome within four years of follow-up after PCI [23]. According to some data, the revascularization technique selection (PCI or CABG) has a significant impact on clinical outcomes in patients with high SYNTAX Score values [24]. However, the disadvantage of these scores is that the tortuosity assessment remains subjective. Considering the fact that coronary artery tortuosity directly affects the vascular bed geometry, intervention complexity, risk of incomplete revascularization and stent thrombosis, the automatic quantitative tortuosity assessment by artificial intelligence methods can be considered as a potential additional parameter to refine the lesion structural complexity. This opens up the possibility for more objective preoperative stratification of patients, optimization of the choice of revascularization tactics and, as a consequence, reduced incidence of ischemic and thrombotic complications.

CONCLUSIONS

The systematic review allowed us to summarize the options for automatic assessement of tortuosity of the coronary, cerebral arteries, aorta and its branches. Arterial tortuosity affects the decision-making tactics when analyzing coronary angiography scans, for example, to assess the possibility of coronary artery stenting or bypass surgery. In this regard, the automatic qualitative tortuosity assessment is important in terms of the speed of decision-making in the operating and preparation rooms. Automatic quantitative assessment of the arterial tortuosity degree is also important, since it can be used as a predictor of adverse cardiovascular events and cerebrovascular disorders.

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