DOI: https://doi.org/10.17816/DD623196

Применение искусственного интеллекта в диагностике кальцификации артерий

Ю.А. Трусов[1], В.С. Чупахина[2], А.С. Нуркаева[3], Н.А. Яковенко[4], И.В. Абленина[5], Р.Ф. Латыпова[5], А.П. Питке[5], А.А. Язовских[3], А.С. Иванов[3], Д.С. Богатырева[6], У.А. Попова[7], А.Ф. Юзлекбаев[3]

[1] Самарский государственный медицинский университет, Самара, Россия;
[2] Ростовский государственный медицинский университет, Ростов-на-Дону, Россия;
[3] Башкирский государственный медицинский университет, Уфа, Россия;
[4] Первый Московский государственный медицинский университет им. И.М. Сеченова, Москва Россия;
[5] Оренбургский государственный медицинский университет, Оренбург, Россия;
[6] Российский национальный исследовательский медицинский университет им. Н.И. Пирогова, Москва, Россия;
[7] Российский университет медицины, Москва, Россия

АННОТАЦИЯ

Обоснование. Показатели заболеваемости населения Российской Федерации патологиями системы кровообращения за прошедшие два десятилетия постоянно повышались, и с 2000 г. до 2019 г. увеличились в 2,047 раза. Процесс кальцификации сосудов включает отложение солей кальция в стенке артерий, что приводит к ремоделированию сосудистой стенки. Лучевые методы исследования — золотой стандарт диагностики кальцификации сосудов. Однако в связи с возрастающим объёмом данных и необходимостью сокращения времени постановки диагноза неизбежно снижается эффективность работы. Активное развитие и внедрение в клиническую практику искусственного интеллекта открыло перед специалистами возможности для решения этих проблем.

Цель — проанализировать отечественную и зарубежную литературу, посвящённую использованию искусственного интеллекта в диагностике различных типов кальцификации сосудов, а также обобщить прогностическую ценность кальцификации сосудов и оценить аспекты, препятствующие диагностике кальцификации сосудов без применения искусственного интеллекта.

Материалы и методы. Авторы провели поиск публикаций в электронных базах данных PubMed, Web of Science, Google Scholar и eLibrary. Поиск проводился по следующим ключевым словам: «artificial intelligence», «machine learning», «vascular calcification», «искусственный интеллект», «машинное обучение», «кальцификация сосудов». Поиск проводился во временном интервале с момента основания соответствующей базы данных до июля 2023 года.

Результаты. Основная методология включённых в обзор исследований заключалась в сравнении диагностических способностей клиницистов и искусственного интеллекта с применением одних и тех же изображений и последующей оценкой точности, скорости и других показателей. Участки возникновения сосудистых кальцификаций весьма разнообразны, что обусловливает их различную прогностическую ценность.

Заключение. Искусственный интеллект отлично зарекомендовал себя в диагностике сосудистой кальцификации. Помимо повышения точности и эффективности, способности к детализации превосходят возможности ручного метода диагностики. Искусственный интеллект достиг уровня, позволяющего помогать врачам инструментальной диагностики в автоматическом выявлении кальцификации сосудов. Возможности искусственного интеллекта могут способствовать эффективному развитию рентгенологии в будущем.

Ключевые слова: искусственный интеллект; машинное обучение; кальцификация сосудов; рентгенология; диагностическая визуализация.

Как цитировать:
Трусов Ю.А., Чупахина В.С., Нуркаева А.С., Яковенко Н.А., Абленина И.В., Латыпова Р.Ф., Питке А.П., Язовских А.А., Иванов А.С., Богатырева Д.С., Попова У.А., Юзлекбаев А.Ф. Применение искусственного интеллекта в диагностике кальцификации артерий // Digital Diagnostics. 2024. Т. 5, № 1. С. 85–100. DOI: https://doi.org/10.17816/DD623196

Рукопись получена: 10.11.2023 **Рукопись одобрена:** 10.01.2024 **Опубликована online:** 29.01.2024

DOI: https://doi.org/10.17816/DD623196

Use of artificial intelligence in the diagnosis of arterial calcification

Yuri A. Trusov[1], Victoria S. Chupakhina[2], Adilya S. Nurkaeva[3], Natalia A. Yakovenko[4], Irina V. Ablenina[5], Roksana F. Latypova[5], Aleksandra P. Pitke[5], Anastasiya A. Yazovskih[3], Artem S. Ivanov[3], Darya S. Bogatyreva[6], Ulyana A. Popova[7], Azat F. Yuzlekbaev[3]

[1] Samara State Medical University, Samara, Russia;
[2] Rostov State Medical University, Rostov-on-Don, Russia;
[3] Bashkir State Medical University, Ufa, Russia;
[4] Sechenov First Moscow State Medical University, Moscow, Russia;
[5] Orenburg State Medical University, Orenburg, Russia;
[6] Russian National Research Medical University named after N.I. Pirogov, Moscow, Russia;
[7] Russian University of Medicine, Moscow, Russia

ABSTRACT

BACKGROUND: The incidence of circulatory system diseases in the Russian Federation has been steadily increasing during the last two decades, growing 2,047 times between 2000 and 2019. Vascular calcification involves the deposition of calcium salts in the artery wall, which leads to vascular wall remodeling. X-ray imaging is the gold standard for diagnosing of vascular calcification. However, because of the need to process an increasing amount of data in a shorter period of time, the number of diagnostic errors inevitably increases, and work efficiency inevitably decreases. The active development and introduction of artificial intelligence into clinical practice have created opportunities for specialists to address these issues.

AIM: To analyze the national and international literature on the use of artificial intelligence in the diagnosis of various vascular calcifications, summarize the prognostic value of vascular calcification, and evaluate aspects that prevent the diagnosis of vascular calcification without using artificial intelligence.

MATERIALS AND METHODS: A search was performed in PubMed, Web of Science, Google Scholar, and eLibrary. The search was conducted using the following keywords: artificial intelligence, machine learning, vascular calcification, and their analogues in Russian. The search covered the period from inception till July 2023.

RESULTS: The studies included in the review compared the diagnostic abilities of clinicians and artificial intelligence using the same images, with subsequent assessment of the accuracy, speed, and other parameters. The sites of vascular calcification varied, resulting in differences in their prognostic value.

CONCLUSION: Artificial intelligence has proven to be effective in the diagnosis of vascular calcification. In addition to improved accuracy and efficiency, the level of detail is superior to manual diagnosis methods. Artificial intelligence has advanced to the point that imaging specialists can automatically detect vascular calcification. Artificial intelligence can contribute to the successful development of X-ray imaging in the future.

Keywords: artificial intelligence; machine learning; vascular calcification; radiology; diagnostic imaging.

To cite this article:
Trusov YuA, Chupakhina VS, Nurkaeva AS, Yakovenko NA, Ablenina IV, Latypova RF, Pitke AP, Yazovskih AA, Ivanov AS, Bogatyreva DS, Popova UA, Yuzlekbaev AF. Use of artificial intelligence in the diagnosis of arterial calcification. *Digital Diagnostics.* 2024;5(1):85–100. DOI: https://doi.org/10.17816/DD623196

Submitted: 10.11.2023 **Accepted:** 10.01.2024 **Published online:** 29.01.2024

DOI: https://doi.org/10.17816/DD623196

人工智能在动脉钙化诊断中的应用

Yuri A. Trusov[1], Victoria S. Chupakhina[2], Adilya S. Nurkaeva[3], Natalia A. Yakovenko[4], Irina V. Ablenina[5], Roksana F. Latypova[5], Aleksandra P. Pitke[5], Anastasiya A. Yazovskih[3], Artem S. Ivanov[3], Darya S. Bogatyreva[6], Ulyana A. Popova[7], Azat F. Yuzlekbaev[3]

[1] Samara State Medical University, Samara, Russia;
[2] Rostov State Medical University, Rostov-on-Don, Russia;
[3] Bashkir State Medical University, Ufa, Russia;
[4] Sechenov First Moscow State Medical University, Moscow, Russia;
[5] Orenburg State Medical University, Orenburg, Russia;
[6] Russian National Research Medical University named after N.I. Pirogov, Moscow, Russia;
[7] Russian University of Medicine, Moscow, Russia

摘要

论证。近二十年来，俄罗斯联邦居民循环系统疾病的发病率持续上升。从2000年到2019年，此类疾病的数量增加了2.047倍。血管钙化过程包括钙盐在动脉壁的沉积，这导致血管壁重塑。放射性检查方法是诊断血管钙化的金标准。然而，随着数据量的增加和诊断时间的需要，工作效率不可避免地下降，人工智能的积极发展和应用于临床为专家解决这些问题提供了机会。

目的。本研究的目的是分析国内外关于使用人工智能诊断不同类型血管钙化的文献，同时，总结血管钙化的预后价值，并评估在不使用人工智能的情况下阻碍血管钙化诊断的方面。

材料与方法。在电子数据库PubMed、Web of Science、Google Scholar和eLibrary中搜索了相关出版物。搜索时使用了以下关键词："artificial intelligence"，"machine learning"，"vascular calcification"，"人工智能"、"机器学习"、"血管钙化"。检索时间为相关数据库建立至2023年7月。

结果。综述中包含的研究的主要方法是比较临床医生和人工智能使用相同图片的诊断能力，然后评估准确性、速度和其他指标。血管钙化发生的部位差异很大，这也是其预后价值不同的原因。

结论。事实证明，人工智能在诊断血管钙化方面表现出色。除了提高准确性和效率外，其细节处理能力也超过人工诊断方法。人工智能已经达到了帮助仪器诊断医生自动检测血管钙化的水平。未来，人工智能的能力可以促进放射学的有效发展。

关键词：人工智能；机器学习；血管钙化；放射学；诊断成像。

引用本文：
Trusov YuA, Chupakhina VS, Nurkaeva AS, Yakovenko NA, Ablenina IV, Latypova RF, Pitke AP, Yazovskih AA, Ivanov AS, Bogatyreva DS, Popova UA, Yuzlekbaev AF. 人工智能在动脉钙化诊断中的应用. *Digital Diagnostics.* 2024;5(1):85–100. DOI: https://doi.org/10.17816/DD623196

收到：10.11.2023 **接受：**10.01.2024 **发布日期：**29.01.2024

BACKGROUND

The incidence of circulatory system diseases in the Russian Federation has been steadily increasing in the last two decades, growing 2.047 times between 2000 and 2019 [1]. Vascular calcification involves the deposition of calcium salts in the arterial wall, which leads to vascular wall remodeling [2]. Intimal calcification is focal and associated with atherosclerosis, whereas medial calcification is diffuse and involved in the pathogenesis of conditions such as diabetes mellitus, peripheral artery disease, and chronic kidney disease [3]. X-ray imaging is the gold standard for diagnosing vascular calcifications [4]. However, because of increasing data and the need to reduce the time for diagnosing, work efficiency inevitably decreases [5]. These circumstances necessitate the search for innovative ways to improve the quality of work of imaging specialists.

The active development and introduction of artificial intelligence (AI) into clinical practice have helped specialists address these issues. According to the available literature, until recently, AI was used for X-ray diagnosis of five types of vascular calcifications: coronary artery calcification (CAC), thoracic aorta calcification (TAC), abdominal aorta calcification (AAC), carotid artery calcification (CaAC), and mammary artery calcification (MAC).

This study aimed to analyze the national and international literature on the use of AI in the diagnosis of various vascular calcifications, summarize the prognostic value of vascular calcification, and evaluate aspects that hinder the diagnosis of vascular calcification without using AI.

MATERIALS AND METHODS

A literature search was performed in PubMed, Web of Science, Google Scholar, and eLibrary. The search was conducted using the following keywords: artificial intelligence, machine learning, vascular calcification, and their equivalents in Russian. The search covered the period from database inception till July 2023. The authors reviewed independently the titles and abstracts of the articles and retrieved the full text of relevant publications. Moreover, the reference lists of relevant studies were reviewed.

RESULTS

The studies included in the review compared the diagnostic abilities of clinicians and AI using the same images and subsequently assessed the accuracy, speed, and other parameters.

The sites of vascular calcification vary greatly, resulting in differences in their prognostic value. Table 1 summarizes the prognostic value of vascular calcifications depending on the location.

Coronary artery calcification

The Framingham risk score is a tool for cardiovascular risk assessment, which includes the assessment of risk factors such as age, sex, and blood pressure [7]. However, a large-scale prospective study with 7 years of follow-up found that CACs detected using computed tomography (CT) can improve the risk prognosis obtained using the Framingham risk score alone. In a study with 7.6 years of follow-up, M.H. Criqui et al. demonstrated a good prognostic value of the assessment of CAC severity based on the vascular volume and density [8]. The risk of coronary artery disease (CAD) positively correlated with the CAC volume and negatively correlated with the CAC density [8].

The CAC severity was assessed by multiplying the density of calcified plaques by the area of calcification. The overall CAC was the sum of the results calculated at each level.

Table 1. Prognostic value of vascular calcifications depending on the location

Vascular calcification type	Prognostic value
Coronary artery calcification	– Marker of the severity of coronary artery atherosclerosis – Cardiovascular risk assessment according to the Framingham risk score – CAD predictor – Marker of chemotherapy-induced cardiotoxicity in patients with cancer
Thoracic aorta calcification	– Marker of increased CAD risk – Detection of an increased risk of ischemic stroke – Embolism risk detection
Abdominal aorta calcification	– Detection of obstructive CAD – Prediction of asymptomatic CAD – Marker of congestive heart failure
Carotid artery calcification	– Marker of atherosclerosis of the head and neck blood vessels – Stroke risk detection – Prediction of the risk of cerebrovascular adverse events in young people
Mammary artery calcification	– Detection of the risk of cardiovascular events in women – Association with chronic kidney disease, diabetes mellitus, and bone diseases

Note: CAD, coronary artery disease.

Table 2. Relationship between the severity of coronary artery calcification and the risk for adverse cardiovascular events

Coronary artery calcification assessment	Calcification risk
0	None
1–10	Low
11–100	Moderate
101–400	Moderate to high
>401	High

Generally, older patients represent a major risk group for CAD [1]. However, a 12.5-year study revealed an increased risk for CAD and death among individuals aged 32–46 years, even in cases of mild CAC [9]. These findings suggest that CAC-related information has a high prognostic value for detecting cardiovascular risk in nearly all age groups. Table 2 shows the relationship between CAC severity and risk for adverse cardiovascular events.

Thoracic aorta calcification

TAC is commonly found in patients with hypertension [10]. Furthermore, recurrent evidence has linked TAC to an increased risk for CAD and death [10, 11]. In a study of 2,618 patients, Y. Itani et al. found that TAC was efficient in ischemic stroke risk assessment [12]. In a study of patients with indications for cardiovascular surgery, R. Lee et al. found that preoperative CT screening for TAC can identify high-risk areas and reduce the risk of aortic embolism and stroke [13]. Thus, TAC severity can be used not only to predict the risk of cardiovascular accidents but also to detect cerebrovascular changes.

Abdominal aorta calcification

A study of 58 patients revealed that CT-AAC assessed AAC correlated with CAC severity. In turn, the absence of AAC made it possible to rule out CAD [14]. Moreover, AAC can be used as an additional tool for detecting asymptomatic CAD and an independent risk factor for congestive heart failure [15, 16]. AAC has a significant prognostic value for the skeletal system. Y.Z. Bagger et al. analyzed 2,662 healthy postmenopausal women and reported that AAC correlated with an increased risk of osteoporosis of the proximal femur [17]. Moreover, in a study of 5,994 men aged 65 years, P. Szulc et al. confirmed the correlation between AAC and an increased risk for femoral fracture in older men [18].

Carotid artery calcification

CaAC is an important predictor of cerebrovascular diseases [19]. Intracranial internal carotid artery calcification (ICAC) is an important marker of intracranial hypertension in patients of various ethnicities and strongly correlated with the risk for stroke [19–21]. A study of approximately 2,000 patients revealed that ICAC was common in young people. However, whether ICAC at a young age is similar to that at an older age is unclear and, therefore, may increase the risk of stroke later in life [22].

Mammary artery calcification

Z. Huang et al. analyzed 213 female patients and revealed that MAC correlated with CAC and CAD severity [23]. EV Bochkareva et al. analyzed 4,274 digital mammograms of women aged 40–93 years and found a significant and strong correlation between age and MAC [24]. E.V. Bochkareva et al. also demonstrated that MAC was associated with chronic kidney disease, diabetes mellitus, cerebrovascular diseases, and low bone mineral density [25–27]. Unfortunately, female patients are often unaware of cardiovascular diseases, which pose one of the most serious threats to women's health [28]. Thus, considering the availability of MAC assessment and its diagnostic value in assessing cardiovascular risk in women, imaging specialists should pay close attention to this issue.

Difficulties in imaging diagnosis of vascular calcifications

An analysis of the evolution of X-ray diagnostic services in Russia in 2014–2019 showed that the number of medical images is increasing annually, and imaging specialists have to interpret images every 3–4 s during an 8-h working day [29]. A study of the physical condition of 40 imaging specialists before and after a working day revealed that after working for 1 day, their ability to concentrate decreases dramatically, whereas symptoms of asthenopathy increase [30]. According to available data, 75% of claims concerning the low quality of medical care provided by imaging specialists are related to diagnostic errors [31].

Accurate assessment of the severity of vascular calcifications is difficult. The shape of the calcified foci is variable, and deviations are common. For example, various modifications of CT scans have been used to diagnose CAC [32]; however, they require additional equipment, increasing the economic burden on healthcare facilities and the patient's radiation exposure (which can be reduced if the diagnosis is made by standard methods). Moreover, radiologists do not always assess vascular calcifications detected on CT scans, which could be used for indirect assessment of coronary calcification. Nonetheless, the gold standard is CT with cardiac synchronization and a specified examination area (field of view) [33, 34].

The role of artificial intelligence in the assessment of arterial calcification

CACs

The first automatic assessment of CAC severity using AI was performed in 2007. For each candidate, 64 features were created, and nearest-neighbor clustering was applied. This metric algorithm for automatic object classification or regression had an accuracy of 73.8% [35]. Since then, various approaches to feature development, including spatial and geometric characteristics, have been actively studied [36–38]. Because selecting objects on noncontrast CT scans is technically challenging, recording information from CT scans with the determination of coronary calcification has become a common strategy [39–41]. To assess coronary calcification, electrocardiographic (ECG) synchronization is commonly used to capture images in the diastolic phase, followed by image reconstruction by stitching. A support vector machine-based algorithm achieved a sensitivity of 98.9% and a prognostic value of 94.8% [42]. Such machine-learning (ML) algorithms were actively used until 2016; however, their use was challenging because of the need for manual control [42].

To further improve efficacy, an artificial neural network (ANN) with deep learning (DL) function was selected as the primary option [43]. DL initially demonstrated low efficacy; however, continuous improvement of the ANN allowed for increased efficacy and accurate, automatic scoring [44–51].

In a study on CAC assessment, B.D. de Vos et al. discovered that the results obtained using DL were nearly identical to those calculated manually. The Agatston score (gold standard of CT calcium scoring in clinical practice) was determined in <0.3 s [52].

The U-Net algorithm is an extension of the ANN intended for more efficient learning requiring fewer resources [53]. N. Gogin et al. confirmed the efficacy of DL based on the U-Net architecture, which proved to be extremely close to the performance of other algorithms [46]. U-Net classified the risks correctly in 86% of cases. Notably, U-Net allows uploading images directly without losing pixel information [49].

CT with cardiac synchronization is less widely used globally than CT without ECG [54]. If the reliability of CAC information obtained without ECG increases, the number of CT scans can be reduced, thus decreasing economic expenditures and radiation exposure [55]. Numerous interferences and artifacts significantly lower the accuracy of manual CAC assessment using CT without ECG [56].

AI has played a significant role in CAC diagnosis using CT without ECG. More than a decade ago, I. Isgum et al. found that ML algorithms ensure the Agatston score assessment with an accuracy of 82.2% when using low-dose chest CT [57]. Many researchers have attempted to level out interference and artifacts and reduce the effect of noncalcified components (stents) on the diagnosis. Their developed DL algorithms allowed for increasing the diagnostic value of low-quality images [58, 59]. According to Z. Sun et al., DL algorithms improved the signal-to-noise ratio of low-dose CT by 27.7% and increased the specificity of CAC detection by 41% by eliminating artifacts [60]. Notably, the rate of correct interpretation of CT without ECG was only 70%; however, the correlation coefficient between the results obtained using AI and manual analysis was 0.923 [56].

B. Yacoub et al. revealed that the sensitivity, specificity, and area under the curve (AUC) of CAC detection on noncontrasted chest CT scans using AI were superior to those of manual assessment. This suggests that AI can be superior to human assessment when analyzing CT findings without ECG [34]. In one study, the efficacy of AI in analyzing CT findings without ECG was confirmed at four study sites. All study samples showed high sensitivity and good prognostic value, which increases the quality of the results [61]. The use of AI in diagnosing CAC based on CT findings without ECG is currently considered a reliable method of assessing data.

Notably, researchers have begun to use AI capabilities to diagnose CAC using other devices, such as when assessing chest X-ray images [62]. P.I. Kamel et al. developed a classification of total calcium parameters on chest X-ray images using deep ANN, making it possible to reduce the need for CT in some patients [63]. In this study, the AUC reached 0.73 and 0.7 in the anteroposterior and lateral images, respectively, when detecting CAC. Moreover, a study proposed a neural network that could analyze invasive coronary angiography images within seconds and detect CAC with a F1 of 0.802 [64].

Thoracic aorta calcification

In contrast to CAC, the accuracy of TAC detection on CT scans does not depend on the heart contraction intensity [65]. For example, in a study by I. Isgum et al., the TAC detection rate was 97.9% when using the k-nearest neighbor method, which correlated with manual findings [65]. In recent years, DL made it possible to detect CAC and TAC simultaneously [66]. Similarly, SGM van Velzen et al. used these methods with various CT modalities (including CT with the determination of coronary calcium, low-dose chest CT, and positron-emission CT), with an intraclass correlation coefficient of 0.68–0.98 [67]. Notably, a sensitivity of 98.4% was observed in a study using a convolutional neural network (CNN) for TAC detection, which made it possible not only to detect TAC in the ascending and descending aorta and the aortic arch but also to assess the risk level [68]. Thus, radiologists now routinely employ AI to automatically assess CAC and TAC.

Abdominal aorta calcification

DL advancements made it possible to automatically detect AAC, which was confirmed in two studies [69, 70]. Dual-energy X-ray absorptiometry is a diagnostic tool that assesses the risk for fractures. The increasingly wide use of this method suggests the possibility of automating AAC assessment; however, because of technical difficulties, it is not routinely used for AAC detection. S. Reid et al. classified AAC using a densitometry-based CNN, with a high degree of agreement with manually obtained findings; the Kappa index was 0.71 [69]. CT provides obvious advantages over dual-energy X-ray absorptiometry for the qualitative assessment of aortic calcification. P.M. Graffy et al. effectively implemented automatic detection of AAC using abdominal CT in >9,000 patients; the authors attributed their success to the use of mask region-based CNN [70]. This study also assessed the prevalence of AAC based on quantitative data, which supports the importance of AI.

In summary, AI can be used to automatically quantify AAC; however, available data are extremely limited.

Carotid artery calcification

CT in combination with AI can be used to detect calcification of both extracranial and intracranial internal carotid arteries [71, 72, 73]. G. Bortsova et al. used four DL networks with a structure similar to that of U-Net. The accuracy of ICAC detection was higher than manual assessment, with a sensitivity of 83.8% and a prognostic value of 88% [73]. Manual assessment of CIC necessitates meticulous analysis; moreover, it is prone to errors, with similar probability (e.g., bone calcification). Given this, the excellent accuracy of DL is of great importance.

Magnetic resonance imaging (MRI) can detect the most significant differences between CaAC and other vascular calcifications [71]. In earlier studies, MRI showed low accuracy in detecting calcifications [71]. However, the use of simultaneous noncontrast angiography and intraplaque hemorrhage (SNAP) has improved the ability to detect calcifications using MRI. SNAP inverts all signals by pulse inversion, followed by T1-weighted inversion recovery and a proton density-weighted control scan with dual gradient echo, providing high-quality images of the cranial and cervical spine arteries [74]. Although SNAP effectively detects calcification, it is prone to motion artifacts and has a long acquisition time. Goal-SNAP and quick SNAP can be used to address this issue [75, 76]. In this study, ML algorithms such as random forest are similar to ANNs in terms of calcification detection; however, DL may be more effective in segmenting vascular components, which requires further research.

Mammary artery calcification

MAC is visualized on mammograms; however, calcifications have extremely diverse manifestations. They can be bifurcated, overlapping, or truncated, with varying intensities [77]. As a result, MAC is difficult to quantify manually because of its heterogeneous presentations.

Mammography is an X-ray diagnosis method used for screening and intended for breast cancer detection. It has been included in the scope of preventive medical examination since 2012. In line with the regulations of the Ministry of Health of the Russian Federation, the frequency of this study increases annually.

Several authors have considered the use of DL in this context. Mammograms were divided into sections because the amount of data was too large for direct entry [53]. The 12-layer CNN defines MAC detection as a second-order task [28]. Although it successfully distinguished the presence and absence of MAC, the accuracy of the quantitative assessment was insufficient [28]. Furthermore, data analysis and processing were time-consuming because of the need to process each segment separately. Subsequently, researchers improved the CNN considering the described drawbacks, suggesting the use of a simple contextual U-Net (SCU-Net) and a dense U-Net (DU-Net) [33, 53]. SCU-Net is a simpler version of U-Net that addresses MAC accounting for <1% of the images, resulting in a significant amount of data and preventing the system's efficient training. DU-Net eliminates this problem by considerably improving the efficacy of the CNN, with an accuracy of 91.47% and a sensitivity of 91.22% [53].

In summary, DL used for automatic MAC detection has advanced considerably; however, no public dataset is available for the unification in this field, which necessitates further studies.

DISCUSSION

AI can facilitate and improve the work of imaging specialists regarding vascular calcification by performing preliminary screening and enhancing data processing efficacy.

The accuracy of AI in X-ray diagnosis was determined by AI algorithms and image characteristics. The efficacy of ML and DL algorithms has improved significantly, increasing the diagnostic value of these techniques. As imaging technology evolves, image quality improves, which intensifies the efficiency of diagnosis. AI capabilities depend on the high quality of databases required for training, which can also be useful in creating public databases or testing platforms. Thus, engineers and physicians should work to improve AI diagnostic capabilities based on AI algorithms and image quality.

Although AI has demonstrated good results in five types of vascular calcifications, it also has potential diagnostic value in renal artery calcification, a condition with confirmed prognostic value for hypertension and proteinuria [79]. Moreover, the number of studies on AAC and CaAC is modest, which increases interest in their research. Table 3 provides a comparison of the efficacy of AI in the diagnosis of each type of vascular calcification.

CONCLUSION

Artificial intelligence has proven to be effective in the diagnosis of vascular calcifications. In addition to improved accuracy and efficiency, its level of detail is superior to that of manual diagnosis methods. AI has advanced to the point that imaging specialists can automatically detect vascular calcification. Artificial intelligence can contribute to the successful development of X-ray imaging in the future.

ADDITIONAL INFORMATION

Funding source. This study was not supported by any external sources of funding.

Competing interests. The authors declare that they have no competing interests.

Table 3. Comparison of the efficacy of AI in the diagnosis of five types of vascular calcification

Vascular calcification type	Number of studies	Use of X-ray imaging	Use of CT	Use of MRI	Use of DL
Coronary artery calcification	Large	Yes	Yes	No	Pixel-based and end-to-end DL in combination with GAN reduces the level of noise and artifacts for a reliable automatic assessment of CAC and interpretation of the results
Thoracic aorta calcification	Moderate	No	Yes	No	DL ensures the automatic detection of TAC and CaAC and enables the assessment of the findings in various portions of the aorta
Abdominal aorta calcification	Small, more studies are required	Yes	Yes	No	DL techniques such as the mask region-CNN enable accurate qualitative assessment of AAC when using DEXA and CT
Carotid artery calcification	Small, more studies are required	No	Yes	Yes	The efficacy of DL is similar to that of ML and superior to human performance, with the added possibility of using MRI
Mammary artery calcification	Moderate	Yes	No	No	U-Net, SCU-Net, DU-Net, and other improved DL systems facilitate MAC detection

Note: AAC, abdominal aorta calcification; CAC, coronary artery calcification; CT, computed tomography DEXA, dual-energy X-ray absorptiometry; DL, deep learning; DU-Net, dense U-Net: GAN, generative adversarial network; MAC, mammary artery calcification; ML, machine learning; MRI, magnetic resonance imaging; Mask region-CNN, mask region-based convolutional neural network; SCU-Net, simple contextual U-Net; TAC, thoracic aorta calcification.

Authors' contribution. All authors made a substantial contribution to the conception of the work, acquisition, analysis, interpretation of data for the work, drafting and revising the work, final approval of the version to be published and agree to be accountable for all aspects of the work. Yu.A. Trusov, V.S. Chupakhina — development of the concept and design of the study, scientific revision of the manuscript; A.S. Nurkaeva — data analysis and search, writing the manuscript; N.A. Yakovenko — data analysis, writing the manuscript; I.V. Ablenina — data analysis, editing the text of the manuscript; R.F. Latypova — data analysis, verification and approval of the text; A.P. Pitke — writing a manuscript, obtaining factual data; A.A. Yazovskikh — editing the text of the article, analyzing data; A.S. Ivanov — obtaining data, writing the text of the article; D.S. Bogatyreva — approval of the final version of the manuscript, editing of the text of the article; U.A. Popova — data analysis, participation in the writing of the article; A.F. Yuzlekbayev — analysis and data acquisition.

REFERENCES

1. Sharapova OV, Kicha DI, Gerasimova LI, et al. Map analysis of morbidity and mortality from blood circulatory system diseases of the population of the Russian federation (2010-2019). *Complex Issues of Cardiovascular Diseases.* 2022;11(1):56–68. EDN: ZUQVNA doi: 10.17802/2306-1278-2022-11-1-56-68

2. Mal'kov OA, Govorukhina AA, Burykin YuG, Afineevskaya AYu. The Role of Calcification in the Pathogenesis of Inflammatory Reaction in the Arterial Wall (Exemplified by the Vessels of the Neck and Head in Adults). *Journal of Medical and Biological Research.* 2021;9(4):435–443. EDN: FTSKDS doi: 10.37482/2687-1491-Z081

3. Archakova TV, Nedosugova LV. Factors of vascular calcification in patients with type 2 diabetes mellitus on long-term dialysis. *Diabetes mellitus*. 2020;23(2):125–131. EDN: KPXIVL doi: 10.14341/DM10145

4. Mori H, Torii S, Kutyna M, et al. Coronary Artery Calcification and its Progression: What Does it Really Mean? *JACC Cardiovasc Imaging.* 2018;11(1):127–142. doi: 10.1016/j.jcmg.2017.10.012

5. Yeo KK. Artificial intelligence in cardiology: did it take off? *Russian Journal for Personalized Medicine.* 2022;2(6):16–22. EDN: UIENOT doi: 10.18705/2782-3806-2022-2-6-16-22

6. Karpov OE, Andrikov DA, Maksimenko VA, Hramov AE. Explainable artificial intelligence for medicine. *Medical Doctor and IT.* 2022;(2):4–11. EDN: DTCAWX doi: 10.25881/18110193_2022_2_4

7. Greenland P, LaBree L, Azen SP, et al. Coronary artery calcium score combined with Framingham score for risk prediction in asymptomatic individuals. *JAMA.* 2004;291(2):210–215. doi: 10.1001/jama.291.2.210

8. Criqui MH, Denenberg JO, Ix JH, et al. Calcium density of coronary artery plaque and risk of incident cardiovascular events. *JAMA.* 2014;311(3):271–278. doi: 10.1001/jama.2013.282535

9. Carr JJ, Jacobs DR Jr, Terry JG, et al. Association of Coronary Artery Calcium in Adults Aged 32 to 46 Years With Incident Coronary Heart Disease and Death. *JAMA Cardiol.* 2017;2(4):391–399. doi: 10.1001/jamacardio.2016.5493

10. Khalikov AA, Kuznetsov KO, Iskuzhina LR, Khalikova LV. Forensic aspects of sudden autopsy-negative cardiac death. *Sudebno-Meditsinskaya Ekspertisa.* 2021;64(3):59–63. doi: 10.17116/sudmed20216403159

11. Eisen A, Tenenbaum A, Koren-Morag N, et al. Calcification of the thoracic aorta as detected by spiral computed tomography among stable angina pectoris patients: association with cardiovascular events and death. *Circulation.* 2008;118(13):1328–1334. doi: 10.1161/CIRCULATIONAHA.107.712141

12. Itani Y, Watanabe S, Masuda Y. Relationship between aortic calcification and stroke in a mass screening program using a mobile helical computed tomography unit. *Circ J.* 2006;70(6):733–736. doi: 10.1253/circj.70.733

13. Lee R, Matsutani N, Polimenakos AC, et al. Preoperative noncontrast chest computed tomography identifies potential aortic emboli. *Ann Thorac Surg.* 2007;84(1):38–42. doi: 10.1016/j.athoracsur.2007.03.025

14. Zweig BM, Sheth M, Simpson S, Al-Mallah MH. Association of abdominal aortic calcium with coronary artery calcium and obstructive coronary artery disease: a pilot study. *Int J Cardiovasc Imaging.* 2012;28(2):399–404. doi: 10.1007/s10554-011-9818-1

15. An C, Lee HJ, Lee HS, et al. CT-based abdominal aortic calcification score as a surrogate marker for predicting the presence of asymptomatic coronary artery disease. *Eur Radiol.* 2014;24(10):2491–2498. doi: 10.1007/s00330-014-3298-3

16. Melnikov MV, Zelinskiy VA, Zhorina AS, Chuglova DA. An abdominal aortic calcification in peripheral arterial occlusive disease: risk factors and markers. *Journal of atherosclerosis and dyslipidemias.* 2014;(3):33–38. EDN: SISNRZ

17. Bagger YZ, Tankó LB, Alexandersen P, et al. Radiographic measure of aorta calcification is a site-specific predictor of bone loss and fracture risk at the hip. *J Intern Med.* 2006;259(6):598–605. doi: 10.1111/j.1365-2796.2006.01640.x

18. Szulc P, Blackwell T, Schousboe JT, et al. High hip fracture risk in men with severe aortic calcification: MrOS study. *J Bone Miner Res.* 2014;29(4):968–975. doi: 10.1002/jbmr.2085

19. Lobanova NI, Chicherina EN, Malchikova SV, Maksimchuk-Kolobova NS. Fluid shear stress on the endothelium of the carotid artery wall and coronary artery calcinosis in patients with arterial hypertension. *South Russian Journal of Therapeutic Practice.* 2022;3(3):60–67. EDN: QWCOCH doi: 10.21886/2712-8156-2022-3-3-60-67

20. Kim JT, Yoo SH, Kwon JH, et al. Subtyping of ischemic stroke based on vascular imaging: analysis of 1,167 acute, consecutive patients. *J Clin Neurol.* 2006;2(4):225–230. doi: 10.3988/jcn.2006.2.4.225

21. Wong LK. Global burden of intracranial atherosclerosis. *Int J Stroke.* 2006;1(3):158–159. doi: 10.1111/j.1747-4949.2006.00045.x

22. Kockelkoren R, De Vis JB, de Jong PA, et al. Intracranial Carotid Artery Calcification From Infancy to Old Age. *J Am Coll Cardiol.* 2018;72(5):582–584. doi: 10.1016/j.jacc.2018.05.021

23. Huang Z, Xiao J, Xie Y, et al. The correlation of deep learning-based CAD-RADS evaluated by coronary computed tomography angiography with breast arterial calcification on mammography. *Sci Rep.* 2020;10(1):11532. doi: 10.1038/s41598-020-68378-4

24. Bochkareva EV, Butina EK, Bayramkulova EKh, et al. Prevalence and Severity of Breast Arterial Calcification on Routine Mammography. *Rational Pharmacotherapy in Cardiology.* 2022;18(5):530–535. EDN: HUFTZE doi: 10.20996/1819-6446-2022-09-01

25. Bochkareva EV, Butina EK, Bayramkulova NKh, Drapkina OM. Mammary artery calcinosis and diabetes mellitus: case report and brief literature review. *Profilakticheskaya Meditsina.* 2021;24(9):97–101. EDN: QPQDLT doi: 10.17116/profmed20212409197

26. Bochkareva EV, Butina EK, Savin AS, et al. Breast arteries calcification: a potential surrogate marker for cerebrovascular disease. *Profilakticheskaya Meditsina.* 2020;23(5):164–169. EDN: IRHLDZ doi: 10.17116/profmed202023051164

27. Bochkareva EV, Butina EK, Savin AS, Drapkina OM. Breast artery calcification and osteoporosis in postmenopausal woman: a case report and opinion on the problem. *Cardiovascular Therapy and Prevention.* 2020;19(4):2574. EDN: RTDDQG doi: 10.15829/1728-8800-2020-2574

28. Wang J, Ding H, Bidgoli FA, et al. Detecting Cardiovascular Disease from Mammograms With Deep Learning. *IEEE Trans Med Imaging.* 2017;36(5):1172–1181. doi: 10.1109/TMI.2017.2655486

29. Golubev NA, Ogryzko EV, Tyurina EM, Shelepova EA, Shelekhov PV. Features of the development of the radiation diagnostics service in the Russian Federation for 2014–2019. *Current problems of health care and medical statistics.* 2021;(2):356–376. EDN: EHSADW doi: 10.24412/2312-2935-2021-2-356-376

30. Krupinski EA, Berbaum KS, Caldwell RT, et al. Long radiology workdays reduce detection and accommodation accuracy. *J Am Coll Radiol.* 2010;7(9):698–704. doi: 10.1016/j.jacr.2010.03.004

31. Lee CS, Nagy PG, Weaver SJ, Newman-Toker DE. Cognitive and system factors contributing to diagnostic errors in radiology. *AJR Am J Roentgenol.* 2013;201(3):611–617. doi: 10.2214/AJR.12.10375

32. Nikolaev AE, Shapiev AN, Blokhin IA, et al. New approaches for assessing coronary changes in multi-layer spiral computed tomography. *Russian Journal of Cardiology.* 2019;(12):124–130. EDN: VHYAYK doi: 10.15829/1560-4071-2019-12-124-130

33. Guo X, O'Neill WC, Vey B, et al. SCU-Net: A deep learning method for segmentation and quantification of breast arterial calcifications on mammograms. *Med Phys.* 2021;48(10):5851–5861. doi: 10.1002/mp.15017

34. Yacoub B, Kabakus IM, Schoepf UJ, et al. Performance of an Artificial Intelligence-Based Platform Against Clinical Radiology Reports for the Evaluation of Noncontrast Chest CT. *Acad Radiol.* 2022;29(2):108–117. doi: 10.1016/j.acra.2021.02.007

35. Isgum I, Rutten A, Prokop M, van Ginneken B. Detection of coronary calcifications from computed tomography scans for automated risk assessment of coronary artery disease. *Med Phys.* 2007;34(4):1450–1461. doi: 10.1118/1.2710548

36. Kurkure U, Chittajallu DR, Brunner G, et al. A supervised classification-based method for coronary calcium detection in non-contrast CT. *Int J Cardiovasc Imaging.* 2010;26(7):817–828. doi: 10.1007/s10554-010-9607-2

37. Brunner G, Chittajallu DR, Kurkure U, Kakadiaris IA. Toward the automatic detection of coronary artery calcification in non-contrast computed tomography data. *Int J Cardiovasc Imaging.* 2010;26(7):829–838. doi: 10.1007/s10554-010-9608-1

38. Brunner G, Kurkure U, Chittajallu DR, et al. Toward unsupervised classification of calcified arterial lesions. *Med Image Comput Comput Assist Interv.* 2008;11(1):144-152. doi: 10.1007/978-3-540-85988-8_18

39. Takx RA, de Jong PA, Leiner T, et al. Automated coronary artery calcification scoring in non-gated chest CT: agreement and reliability. *PLoS One.* 2014;9(3):e91239. doi: 10.1371/journal.pone.0091239

40. Wolterink JM, Leiner T, Takx RA, et al. Automatic Coronary Calcium Scoring in Non-Contrast-Enhanced ECG-Triggered Cardiac CT With Ambiguity Detection. *IEEE Trans Med Imaging.* 2015;34(9):1867–1878. doi: 10.1109/TMI.2015.2412651

41. Saur SC, Alkadhi H, Desbiolles L, et al. Automatic detection of calcified coronary plaques in computed tomography data sets. *Med Image Comput Comput Assist Interv.* 2008;11(1):170–177. doi: 10.1007/978-3-540-85988-8_21

42. Yang G, Chen Y, Ning X, et al. Automatic coronary calcium scoring using noncontrast and contrast CT images. *Med Phys.* 2016;43(5):2174. doi: 10.1118/1.4945045

43. Jiang B, Guo N, Ge Y, et al. Development and application of artificial intelligence in cardiac imaging. *Br J Radiol.* 2020;93(1113):20190812. doi: 10.1259/bjr.20190812

44. Shahzad R, van Walsum T, Schaap M, et al. Vessel specific coronary artery calcium scoring: an automatic system. *Acad Radiol.* 2013;20(1):1–9. doi: 10.1016/j.acra.2012.07.018

45. Cano-Espinosa C, González G, Washko GR, et al. Automated Agatston Score Computation in non-ECG Gated CT Scans Using Deep Learning. *Proc SPIE Int Soc Opt Eng.* 2018;10574:105742K. doi: 10.1117/12.2293681

46. Gogin N, Viti M, Nicodème L, et al. Automatic coronary artery calcium scoring from unenhanced-ECG-gated CT using deep learning. *Diagn Interv Imaging.* 2021;102(11):683–690. doi: 10.1016/j.diii.2021.05.004

47. Wolterink JM, Leiner T, de Vos BD, et al. Automatic coronary artery calcium scoring in cardiac CT angiography using paired convolutional neural networks. *Med Image Anal.* 2016;34:123–136. doi: 10.1016/j.media.2016.04.004

48. Wang W, Wang H, Chen Q, et al. Coronary artery calcium score quantification using a deep-learning algorithm. *Clin Radiol.* 2020;75(3):237.e11–237.e16. doi: 10.1016/j.crad.2019.10.012

49. Singh G, Al'Aref SJ, Lee BC, et al. End-to-End, Pixel-Wise Vessel-Specific Coronary and Aortic Calcium Detection and Scoring Using Deep Learning. *Diagnostics (Basel).* 2021;11(2):215. doi: 10.3390/diagnostics11020215

50. Martin SS, van Assen M, Rapaka S, et al. Evaluation of a Deep Learning-Based Automated CT Coronary Artery Calcium Scoring Algorithm. *JACC Cardiovasc Imaging.* 2020;13(1):524–526. doi: 10.1016/j.jcmg.2019.09.015

51. Zhang N, Yang G, Zhang W, et al. Fully automatic framework for comprehensive coronary artery calcium scores analysis on non-contrast cardiac-gated CT scan: Total and vessel-specific quantifications. *Eur J Radiol.* 2021;134:109420. doi: 10.1016/j.ejrad.2020.109420

52. de Vos BD, Wolterink JM, Leiner T, et al. Direct Automatic Coronary Calcium Scoring in Cardiac and Chest CT. I*EEE Trans Med Imaging.* 2019;38(9):2127–2138. doi: 10.1109/TMI.2019.2899534

53. AlGhamdi M, Abdel-Mottaleb M, Collado-Mesa F. DU-Net: Convolutional Network for the Detection of Arterial Calcifications in Mammograms. *IEEE Trans Med Imaging.* 2020;39(10):3240–3249. doi: 10.1109/TMI.2020.2989737

54. Nikolaev AE, Korkunova OA, Khutornoy IV, et al. Comparability of coronary risk assessment methods with chest ultra-LDCT and CT coronography with ECG synchronization. *Medical Visualization.* 2021;25(4):75–92. EDN: CMSGAX doi: 10.24835/1607-0763-1047

55. van Assen M, Martin SS, Varga-Szemes A, et al. Automatic coronary calcium scoring in chest CT using a deep neural network in direct comparison with non-contrast cardiac CT: A validation study. *Eur J Radiol.* 2021;134:109428. doi: 10.1016/j.ejrad.2020.109428

56. Nikolaev AE, Shapiev AN, Blokhin IA. Standardization of coronary artery calcification assessment on contrast-free computed tomograms without ECG synchronization. *Radiology Study.* 2020;3(2):45–52. EDN: VVGXBI

57. Isgum I, Prokop M, Niemeijer M, et al. Automatic coronary calcium scoring in low-dose chest computed tomography. *IEEE Trans Med Imaging.* 2012;31(12):2322–2334. doi: 10.1109/TMI.2012.2216889

58. Wolterink JM, Leiner T, Viergever MA, Isgum I. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. *IEEE Trans Med Imaging.* 2017;36(12):2536–2545. doi: 10.1109/TMI.2017.2708987

59. Klug M, Shemesh J, Green M, et al. A deep-learning method for the denoising of ultra-low dose chest CT in coronary artery calcium score evaluation. *Clin Radiol.* 2022;77(7):509–517. doi: 10.1016/j.crad.2022.03.005

60. Sun Z, Ng CKC. Artificial Intelligence (Enhanced Super-Resolution Generative Adversarial Network) for Calcium Deblooming in Coronary Computed Tomography Angiography: A Feasibility Study. *Diagnostics (Basel).* 2022;12(4):991. doi: 10.3390/diagnostics12040991

61. Eng D, Chute C, Khandwala N, et al. Automated coronary calcium scoring using deep learning with multicenter external validation. *NPJ Digit Med.* 2021;4(1):88. doi: 10.1038/s41746-021-00460-1

62. Morozov SP, Kokina DYu, Pavlov NA, et al. Clinical aspects of using artificial intelligence for the interpretation of chest X-rays. *Tuberculosis and Lung Diseases.* 2021;99(4):58–64. doi: 10.21292/2075-1230-2021-99-4-58-64

63. Kamel PI, Yi PH, Sair HI, Lin CT. Prediction of Coronary Artery Calcium and Cardiovascular Risk on Chest Radiographs Using Deep Learning. *Radiol Cardiothorac Imaging.* 2021;3(3):e200486. doi: 10.1148/ryct.2021200486

64. Du T, Xie L, Zhang H, et al. Training and validation of a deep learning architecture for the automatic analysis of coronary angiography. *EuroIntervention.* 2021;17(1):32–40. doi: 10.4244/EIJ-D-20-00570

65. Isgum I, Rutten A, Prokop M, et al. Automated aortic calcium scoring on low-dose chest computed tomography. *Med Phys.* 2010;37(2):714–723. doi: 10.1118/1.3284211

66. de Vos BD, Lessmann N, de Jong PA, Išgum I. Deep Learning-Quantified Calcium Scores for Automatic Cardiovascular Mortality Prediction at Lung Screening Low-Dose CT. *Radiol Cardiothorac Imaging.* 2021;3(2):e190219. doi: 10.1148/ryct.2021190219

67. van Velzen SGM, Lessmann N, Velthuis BK, et al. Deep Learning for Automatic Calcium Scoring in CT: Validation Using Multiple Cardiac CT and Chest CT Protocols. *Radiology.* 2020;295(1):66–79. doi: 10.1148/radiol.2020191621

68. Guilenea FN, Casciaro ME, Pascaner AF, et al. Thoracic Aorta Calcium Detection and Quantification Using Convolutional Neural Networks in a Large Cohort of Intermediate-Risk Patients. *Tomography.* 2021;7(4):636–649. doi: 10.3390/tomography7040054

69. Reid S, Schousboe JT, Kimelman D, et al. Machine learning for automated abdominal aortic calcification scoring of DXA vertebral fracture assessment images: A pilot study. *Bone.* 2021;148:115943. doi: 10.1016/j.bone.2021.115943

70. Graffy PM, Liu J, O'Connor S, et al. Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort. *Abdom Radiol (NY).* 2019;44(8):2921–2928. doi: 10.1007/s00261-019-02014-2

71. van Engelen A, Niessen WJ, Klein S, et al. Atherosclerotic plaque component segmentation in combined carotid MRI and CTA data incorporating class label uncertainty. *PLoS One.* 2014;9(4):e94840. doi: 10.1371/journal.pone.0094840

72. Onishchenko PS, Klyshnikov KYu, Ovcharenko EA. Artificial neural networks in cardiology: analysis of graphic data. *Bulletin of Siberian Medicine.* 2021;20(4):193–204. EDN: XVBERA doi: 10.20538/1682-0363-2021-4-193-204

73. Bortsova G, Bos D, Dubost F, et al. Automated Segmentation and Volume Measurement of Intracranial Internal Carotid Artery Calcification at Noncontrast CT. *Radiol Artif Intell.* 2021;3(5):e200226. doi: 10.1148/ryai.2021200226

74. Li D, Qiao H, Han Y, et al. Histological validation of simultaneous non-contrast angiography and intraplaque hemorrhage imaging (SNAP) for characterizing carotid intraplaque hemorrhage. *Eur Radiol.* 2021;31(5):3106–3115. doi: 10.1007/s00330-020-07352-0

75. Chen S, Ning J, Zhao X, et al. Fast simultaneous noncontrast angiography and intraplaque hemorrhage (fSNAP) sequence for carotid artery imaging. *Magn Reson Med.* 2017;77(2):753–758. doi: 10.1002/mrm.26111

76. Qi H, Sun J, Qiao H, et al. Carotid Intraplaque Hemorrhage Imaging with Quantitative Vessel Wall T1 Mapping: Technical Development and Initial Experience. *Radiology.* 2018;287(1):276–284. doi: 10.1148/radiol.2017170526

77. Cheng JZ, Cole EB, Pisano ED, Shen D. Detection of arterial calcification in mammograms by random walks. *Inf Process Med Imaging.* 2009;21:713–724. doi: 10.1007/978-3-642-02498-6_59

78. Lomakov SYu. Volumes of mammographic studies in modern conditions of providing preventive measures. *Profilakticheskaya Meditsina*. 2020;23(4):41–44. EDN: OUUINQ doi: 10.17116/profmed20202304141

79. Roseman DA, Hwang SJ, Manders ES, et al. Renal artery calcium, cardiovascular risk factors, and indexes of renal function. *Am J Cardiol.* 2014;113(1):156–161. doi: 10.1016/j.amjcard.2013.09.036

СПИСОК ЛИТЕРАТУРЫ

1. Шарапова О.В., Кича Д.И., Герасимова Л.И., и др. Картографический анализ показателей заболеваемости и смертности от болезней системы кровообращения населения Российской Федерации (2010-2019 гг.) // Комплексные проблемы сердечно-сосудистых заболеваний. 2022. Т. 11, № 1. С. 56–68. EDN: ZUQVNA doi: 10.17802/2306-1278-2022-11-1-56-68

2. Мальков О.А., Говорухина А.А., Бурыкин Ю.Г., Афинеевская А.Ю. Роль кальцификации в патогенезе воспалительной реакции артериальной стенки (на примере сосудов шеи и головы взрослого населения) // Журнал медико-биологических исследований. 2021. Т. 9, № 4. С. 435–443. EDN: FTSKDS doi: 10.37482/2687-1491-Z081

3. Арчакова Т.В., Недосугова Л.В. Факторы кальцификации сосудов у пациентов с сахарным диабетом 2 типа, получающих лечение программным гемодиализом // Сахарный диабет. 2020. Т. 23, № 2. С. 125–131. EDN: KPXIVL doi: 10.14341/DM10145

4. Mori H, Torii S, Kutyna M, et al. Coronary Artery Calcification and its Progression: What Does it Really Mean? // JACC Cardiovasc Imaging. 2018. Vol. 11, N 1. P. 127–142. doi: 10.1016/j.jcmg.2017.10.012

5. Йео К.К. Искусственный интеллект в кардиологии: сработал ли он? // Российский журнал персонализированной медицины. 2022. Т. 2, № 6. С. 16–22. EDN: UIENOT doi: 10.18705/2782-3806-2022-2-6-16-22

6. Карпов О.Э., Андриков Д.А., Максименко В.А., Храмов А.Е. Прозрачный искусственный интеллект для медицины // Врач и информационные технологии. 2022. № 2. С. 4–11. EDN: DTCAWX doi: 10.25881/18110193_2022_2_4

7. Greenland P., LaBree L., Azen S.P., et al. Coronary artery calcium score combined with Framingham score for risk prediction in asymptomatic individuals // JAMA. 2004. Vol. 291, N 2. P. 210–215. doi: 10.1001/jama.291.2.210

8. Criqui M.H., Denenberg J.O., Ix J.H., et al. Calcium density of coronary artery plaque and risk of incident cardiovascular events // JAMA. 2014. Vol. 311, N 3. P. 271–278. doi: 10.1001/jama.2013.282535

9. Carr J.J., Jacobs D.R. Jr, Terry J.G., et al. Association of Coronary Artery Calcium in Adults Aged 32 to 46 Years With Incident Coronary Heart Disease and Death // JAMA Cardiol. 2017. Vol. 2, N 4. P. 391–399. doi: 10.1001/jamacardio.2016.5493

10. Халиков А.А., Кузнецов К.О., Искужина Л.Р., и др. Судебно-медицинские аспекты внезапной аутопсия-отрицательной сердечной смерти // Судебно-медицинская экспертиза. 2021. Т. 64, № 3. С. 59–63. doi: 10.17116/sudmed20216403159

11. Eisen A., Tenenbaum A., Koren-Morag N., et al. Calcification of the thoracic aorta as detected by spiral computed tomography among stable angina pectoris patients: association with cardiovascular events and death // Circulation. 2008. Vol. 118, N 13. P. 1328–1334. doi: 10.1161/CIRCULATIONAHA.107.712141

12. Itani Y., Watanabe S., Masuda Y. Relationship between aortic calcification and stroke in a mass screening program using a mobile helical computed tomography unit // Circ J. 2006. Vol. 70, N 6. P. 733–736. doi: 10.1253/circj.70.733

13. Lee R., Matsutani N., Polimenakos A.C., et al. Preoperative noncontrast chest computed tomography identifies potential aortic emboli // Ann Thorac Surg. 2007. Vol. 84, N 1. P. 38–42. doi: 10.1016/j.athoracsur.2007.03.025

14. Zweig B.M., Sheth M., Simpson S., Al-Mallah M.H. Association of abdominal aortic calcium with coronary artery calcium and obstructive coronary artery disease: a pilot study // Int J Cardiovasc Imaging. 2012. Vol. 28, N 2. P. 399–404. doi: 10.1007/s10554-011-9818-1

15. An C., Lee H.J., Lee H.S., et al. CT-based abdominal aortic calcification score as a surrogate marker for predicting the presence of asymptomatic coronary artery disease // Eur Radiol. 2014. Vol. 24, N 10. P. 2491–2498. doi: 10.1007/s00330-014-3298-3

16. Мельников М.В., Зелинский В.А., Жорина А.С., Чуглова Д.А. Кальцификация абдоминальной аорты при периферическом атеросклерозе: факторы риска и маркёры // Атеросклероз и дислипидемии. 2014. № 3. С. 33–38. EDN: SISNRZ

17. Bagger Y.Z., Tankó L.B., Alexandersen P., et al. Radiographic measure of aorta calcification is a site-specific predictor of bone loss and fracture risk at the hip // J Intern Med. 2006. Vol. 259, N 6. P. 598–605. doi: 10.1111/j.1365-2796.2006.01640.x

18. Szulc P., Blackwell T., Schousboe J.T., et al. High hip fracture risk in men with severe aortic calcification: MrOS study // J Bone Miner Res. 2014. Vol. 29, N 4. P. 968–975. doi: 10.1002/jbmr.2085

19. Лобанова Н.Ю., Чичерина Е.Н., Мальчикова С.В., Максимчук-Колобова Н.С. Напряжение сдвига на эндотелии стенки сонной артерии и кальциноз коронарных артерий у пациентов с гипертонической болезнью // Южно-Российский журнал терапевтической практики. 2022. Т. 3, № 3. С. 60–67. EDN: QWCOCH doi: 10.21886/2712-8156-2022-3-3-60-67

20. Kim J.T., Yoo S.H., Kwon J.H., et al. Subtyping of ischemic stroke based on vascular imaging: analysis of 1,167 acute, consecutive patients // J Clin Neurol. 2006. Vol. 2, N 4. P. 225–230. doi: 10.3988/jcn.2006.2.4.225

21. Wong L.K. Global burden of intracranial atherosclerosis // Int J Stroke. 2006. Vol. 1, N 3. P. 158–159. doi: 10.1111/j.1747-4949.2006.00045.x

22. Kockelkoren R., De Vis J.B., de Jong P.A., et al. Intracranial Carotid Artery Calcification From Infancy to Old Age // J Am Coll Cardiol. 2018. Vol. 72, N 5. P. 582–584. doi: 10.1016/j.jacc.2018.05.021

23. Huang Z., Xiao J., Xie Y., et al. The correlation of deep learning-based CAD-RADS evaluated by coronary computed tomography angiography with breast arterial calcification on mammography // Sci Rep. 2020. Vol. 10, N 1. P. 11532. doi: 10.1038/s41598-020-68378-4

24. Бочкарева Е.В., Бутина Е.К., Байрамкулова Н.Х., и др. Распространенность и степень тяжести кальциноза артерий молочной железы — нового маркёра сердечно-сосудистого риска у женщин // Рациональная Фармакотерапия в Кардиологии. 2022. Т. 18, № 5. С. 530–535. EDN: HUFTZE doi: 10.20996/1819-6446-2022-09-01

25. Бочкарева Е.В., Бутина Е.К., Байрамкулова Н.Х., Драпкина О.М. Кальциноз артерий молочной железы и сахарный диабет: клинический пример и краткий обзор литературы // Профилактическая медицина. 2021. Т. 24, № 9. С. 97–101. EDN: QPQDLT doi: 10.17116/profmed20212409197

26. Бочкарева Е.В., Бутина Е.К., Савин А.С., и др. Кальциноз артерий молочной железы: потенциальный суррогатный маркёр цереброваскулярных заболеваний // Профилактическая медицина. 2020. Т. 23, № 5. С. 164–169. EDN: IRHLDZ doi: 10.17116/profmed202023051164

27. Бочкарева Е.В., Бутина Е.К., Савин А.С., Драпкина О.М. Кальциноз артерий молочной железы и остеопороз у женщины в постменопаузе (клинический случай и мнение по проблеме) // Кардиоваскулярная терапия и профилактика. 2020. Т. 19, № 4. С. 2574. EDN: RTDDQG doi: 10.15829/1728-8800-2020-2574

28. Wang J., Ding H., Bidgoli F.A., et al. Detecting Cardiovascular Disease from Mammograms With Deep Learning // IEEE Trans Med Imaging. 2017. Vol. 36, N 5. P. 1172–1181. doi: 10.1109/TMI.2017.2655486

29. Голубев Н.А., Огрызко Е.В., Тюрина Е.М., Шелепова Е.А., Шелехов П.В. Особенности развития службы лучевой диагностики в Российской Федерации за 2014–2019 года // Современные проблемы здравоохранения и медицинской статистики. 2021. № 2. С. 356–376. EDN: EHSADW doi: 10.24412/2312-2935-2021-2-356-376

30. Krupinski E.A., Berbaum K.S., Caldwell R.T., et al. Long radiology workdays reduce detection and accommodation accuracy // J Am Coll Radiol. 2010. Vol. 7, N 9. P. 698–704. doi: 10.1016/j.jacr.2010.03.004

31. Lee C.S., Nagy P.G., Weaver S.J., Newman-Toker D.E. Cognitive and system factors contributing to diagnostic errors in radiology // AJR Am J Roentgenol. 2013. Vol. 201, N 3. P. 611–617. doi: 10.2214/AJR.12.10375

32. Николаев А.Е., Шапиев А.Н., Блохин И.А., и др. Новые подходы к оценке изменений коронарных артерий при мультиспиральной компьютерной томографии // Российский кардиологический журнал. 2019. № 12. С. 124–130. EDN: VHYAYK doi: 10.15829/1560-4071-2019-12-124-130

33. Guo X., O'Neill W.C., Vey B., et al. SCU-Net: A deep learning method for segmentation and quantification of breast arterial calcifications on mammograms // Med Phys. 2021. Vol. 48, N 10. P. 5851–5861. doi: 10.1002/mp.15017

34. Yacoub B., Kabakus I.M., Schoepf U.J., et al. Performance of an Artificial Intelligence-Based Platform Against Clinical Radiology Reports for the Evaluation of Noncontrast Chest CT // Acad Radiol. 2022. Vol. 29, N 2. P. 108–117. doi: 10.1016/j.acra.2021.02.007

35. Isgum I., Rutten A., Prokop M., van Ginneken B. Detection of coronary calcifications from computed tomography scans for automated risk assessment of coronary artery disease // Med Phys. 2007. Vol. 34, N 4. P. 1450–1461. doi: 10.1118/1.2710548

36. Kurkure U., Chittajallu D.R., Brunner G., et al. A supervised classification-based method for coronary calcium detection in non-contrast CT // Int J Cardiovasc Imaging. 2010. Vol. 26, N 7. P. 817–828. doi: 10.1007/s10554-010-9607-2

37. Brunner G., Chittajallu D.R., Kurkure U., Kakadiaris I.A. Toward the automatic detection of coronary artery calcification in non-contrast computed tomography data // Int J Cardiovasc Imaging. 2010. Vol. 26, N 7. P. 829–838. doi: 10.1007/s10554-010-9608-1

38. Brunner G., Kurkure U., Chittajallu D.R., et al. Toward unsupervised classification of calcified arterial lesions // Med Image Comput Comput Assist Interv. 2008. Vol. 11, N 1. P. 144-152. doi: 10.1007/978-3-540-85988-8_18

39. Takx R.A., de Jong P.A., Leiner T., et al. Automated coronary artery calcification scoring in non-gated chest CT: agreement and reliability // PLoS One. 2014. Vol. 9, N 3. P. e91239. doi: 10.1371/journal.pone.0091239

40. Wolterink J.M., Leiner T., Takx R.A., et al. Automatic Coronary Calcium Scoring in Non-Contrast-Enhanced ECG-Triggered Cardiac CT With Ambiguity Detection // IEEE Trans Med Imaging. 2015. Vol. 34, N 9. P. 1867–1878. doi: 10.1109/TMI.2015.2412651

41. Saur S.C., Alkadhi H., Desbiolles L., et al. Automatic detection of calcified coronary plaques in computed tomography data sets // Med Image Comput Comput Assist Interv. 2008. Vol. 11, N 1. P. 170–177. doi: 10.1007/978-3-540-85988-8_21

42. Yang G., Chen Y., Ning X., et al. Automatic coronary calcium scoring using noncontrast and contrast CT images // Med Phys. 2016. Vol. 43, N 5. P. 2174. doi: 10.1118/1.4945045

43. Jiang B., Guo N., Ge Y., et al. Development and application of artificial intelligence in cardiac imaging // Br J Radiol. 2020. Vol. 93, N 1113. P. 20190812. doi: 10.1259/bjr.20190812

44. Shahzad R., van Walsum T., Schaap M., et al. Vessel specific coronary artery calcium scoring: an automatic system // Acad Radiol. 2013. Vol. 20, N 1. P. 1–9. doi: 10.1016/j.acra.2012.07.018

45. Cano-Espinosa C., González G., Washko G.R., et al. Automated Agatston Score Computation in non-ECG Gated CT Scans Using Deep Learning // Proc SPIE Int Soc Opt Eng. 2018. Vol. 10574. P. 105742K. doi: 10.1117/12.2293681

46. Gogin N., Viti M., Nicodème L., et al. Automatic coronary artery calcium scoring from unenhanced-ECG-gated CT using deep learning // Diagn Interv Imaging. 2021. Vol. 102, N 11. P. 683–690. doi: 10.1016/j.diii.2021.05.004

47. Wolterink J.M., Leiner T., de Vos B.D., et al. Automatic coronary artery calcium scoring in cardiac CT angiography using paired convolutional neural networks // Med Image Anal. 2016. Vol. 34. P. 123–136. doi: 10.1016/j.media.2016.04.004

48. Wang W., Wang H., Chen Q., et al. Coronary artery calcium score quantification using a deep-learning algorithm // Clin Radiol. 2020. Vol. 75, N 3. P. 237.e11–237.e16. doi: 10.1016/j.crad.2019.10.012

49. Singh G., Al'Aref S.J., Lee B.C., et al. End-to-End, Pixel-Wise Vessel-Specific Coronary and Aortic Calcium Detection and Scoring Using Deep Learning // Diagnostics (Basel). 2021. Vol. 11, N 2. P. 215. doi: 10.3390/diagnostics11020215

50. Martin S.S., van Assen M., Rapaka S., et al. Evaluation of a Deep Learning-Based Automated CT Coronary Artery Calcium Scoring Algorithm // JACC Cardiovasc Imaging. 2020. Vol. 13, N 1. P. 524–526. doi: 10.1016/j.jcmg.2019.09.015

51. Zhang N., Yang G., Zhang W., et al. Fully automatic framework for comprehensive coronary artery calcium scores analysis on non-contrast cardiac-gated CT scan: Total and vessel-specific quantifications // Eur J Radiol. 2021. Vol. 134. P. 109420. doi: 10.1016/j.ejrad.2020.109420

52. de Vos B.D., Wolterink J.M., Leiner T., et al. Direct Automatic Coronary Calcium Scoring in Cardiac and Chest CT // IEEE Trans Med Imaging. 2019. Vol. 38, N 9. P. 2127–2138. doi: 10.1109/TMI.2019.2899534

53. AlGhamdi M., Abdel-Mottaleb M., Collado-Mesa F. DU-Net: Convolutional Network for the Detection of Arterial Calcifications in Mammograms // IEEE Trans Med Imaging. 2020. Vol. 39, N 10. P. 3240–3249. doi: 10.1109/TMI.2020.2989737

54. Николаев А.Е., Коркунова О.А., Хуторной И.В., и др. Сопоставимость методик оценки коронарных рисков по данным ультра-НДКТ грудной клетки и КТ-коронарографии с ЭКГ-синхронизацией // Медицинская визуализация. 2021. Т. 25, № 4. С. 75–92. EDN: CMSGAX doi: 10.24835/1607-0763-1047

55. van Assen M., Martin S.S., Varga-Szemes A., et al. Automatic coronary calcium scoring in chest CT using a deep neural network in direct comparison with non-contrast cardiac CT: A validation study // Eur J Radiol. 2021. Vol. 134. P. 109428. doi: 10.1016/j.ejrad.2020.109428

56. Николаев А.Е., Шапиев А.Н., Блохин И.А. Стандартизация оценки кальцификации коронарных артерий на бесконтрастных компьютерных томограммах без ЭКГ-синхронизации // Radiology Study. 2020. Т. 3, № 2. С. 45–52. EDN: VVGXBI

57. Isgum I., Prokop M., Niemeijer M., et al. Automatic coronary calcium scoring in low-dose chest computed tomography // IEEE Trans Med Imaging. 2012. Vol. 31, N 12. P. 2322–2334. doi: 10.1109/TMI.2012.2216889

58. Wolterink J.M., Leiner T., Viergever M.A., Isgum I. Generative Adversarial Networks for Noise Reduction in Low-Dose CT // IEEE Trans Med Imaging. 2017. Vol. 36, N 12. P. 2536–2545. doi: 10.1109/TMI.2017.2708987

59. Klug M., Shemesh J., Green M., et al. A deep-learning method for the denoising of ultra-low dose chest CT in coronary artery calcium score evaluation // Clin Radiol. 2022. Vol. 77, N 7. P. 509–517. doi: 10.1016/j.crad.2022.03.005

60. Sun Z., Ng C.K.C. Artificial Intelligence (Enhanced Super-Resolution Generative Adversarial Network) for Calcium Deblooming in Coronary Computed Tomography Angiography: A Feasibility Study // Diagnostics (Basel). 2022. Vol. 12, N 4. P. 991. doi: 10.3390/diagnostics12040991

61. Eng D., Chute C., Khandwala N., et al. Automated coronary calcium scoring using deep learning with multicenter external validation // NPJ Digit Med. 2021. Vol. 4, N 1. P. 88. doi: 10.1038/s41746-021-00460-1

62. Морозов С.П., Кокина Д.Ю., Павлов Н.А., и др. Клинические аспекты применения искусственного интеллекта для интерпретации рентгенограмм органов грудной клетки // Туберкулез и болезни легких. 2021. Т. 99, № 4. С. 58–64. doi: 10.21292/2075-1230-2021-99-4-58-64

63. Kamel P.I., Yi P.H., Sair H.I., Lin C.T. Prediction of Coronary Artery Calcium and Cardiovascular Risk on Chest Radiographs Using Deep Learning // Radiol Cardiothorac Imaging. 2021. Vol. 3, N 3. P. e200486. doi: 10.1148/ryct.2021200486

64. Du T., Xie L., Zhang H., et al. Training and validation of a deep learning architecture for the automatic analysis of coronary angiography // EuroIntervention. 2021. Vol. 17, N 1. P. 32–40. doi: 10.4244/EIJ-D-20-00570

65. Isgum I., Rutten A., Prokop M., et al. Automated aortic calcium scoring on low-dose chest computed tomography // Med Phys. 2010. Vol. 37, N 2. P. 714–723. doi: 10.1118/1.3284211

66. de Vos B.D., Lessmann N., de Jong P.A., Išgum I. Deep Learning-Quantified Calcium Scores for Automatic Cardiovascular Mortality Prediction at Lung Screening Low-Dose CT // Radiol Cardiothorac Imaging. 2021. Vol. 3, N 2. P. e190219. doi: 10.1148/ryct.2021190219

67. van Velzen S.G.M., Lessmann N., Velthuis B.K., et al. Deep Learning for Automatic Calcium Scoring in CT: Validation Using Multiple Cardiac CT and Chest CT Protocols // Radiology. 2020. Vol. 295, N 1. P. 66–79. doi: 10.1148/radiol.2020191621

68. Guilenea F.N., Casciaro M.E., Pascaner A.F., et al. Thoracic Aorta Calcium Detection and Quantification Using Convolutional Neural Networks in a Large Cohort of Intermediate-Risk Patients // Tomography. 2021. Vol. 7, N 4. P. 636–649. doi: 10.3390/tomography7040054

69. Reid S., Schousboe J.T., Kimelman D., et al. Machine learning for automated abdominal aortic calcification scoring of DXA vertebral fracture assessment images: A pilot study // Bone. 2021. Vol. 148. P. 115943. doi: 10.1016/j.bone.2021.115943

70. Graffy P.M., Liu J., O'Connor S., et al. Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort // Abdom Radiol (NY). 2019. Vol. 44, N 8. P. 2921–2928. doi: 10.1007/s00261-019-02014-2

71. van Engelen A., Niessen W.J., Klein S., et al. Atherosclerotic plaque component segmentation in combined carotid MRI and CTA data incorporating class label uncertainty // PLoS One. 2014. Vol. 9, N 4. P. e94840. doi: 10.1371/journal.pone.0094840

72. Онищенко П.С., Клышников К.Ю., Овчаренко Е.А. Искусственные нейронные сети в кардиологии: анализ графических данных // Бюллетень сибирской медицины. 2021. Т. 20, № 4. С. 193–204. EDN: XVBERA doi: 10.20538/1682-0363-2021-4-193-204

73. Bortsova G., Bos D., Dubost F., et al. Automated Segmentation and Volume Measurement of Intracranial Internal Carotid Artery Calcification at Noncontrast CT // Radiol Artif Intell. 2021. Vol. 3, N 5. P. e200226. doi: 10.1148/ryai.2021200226

74. Li D., Qiao H., Han Y., et al. Histological validation of simultaneous non-contrast angiography and intraplaque hemorrhage imaging (SNAP) for characterizing carotid intraplaque hemorrhage // Eur Radiol. 2021. Vol. 31, N 5. P. 3106–3115. doi: 10.1007/s00330-020-07352-0

75. Chen S., Ning J., Zhao X., et al. Fast simultaneous noncontrast angiography and intraplaque hemorrhage (fSNAP) sequence for carotid artery imaging // Magn Reson Med. 2017. Vol. 77, N 2. P. 753–758. doi: 10.1002/mrm.26111

76. Qi H., Sun J., Qiao H., et al. Carotid Intraplaque Hemorrhage Imaging with Quantitative Vessel Wall T1 Mapping: Technical Development and Initial Experience // Radiology. 2018. Vol. 287, N 1. P. 276–284. doi: 10.1148/radiol.2017170526

77. Cheng J.Z., Cole E.B., Pisano E.D., Shen D. Detection of arterial calcification in mammograms by random walks // Inf Process Med Imaging. 2009. Vol. 21. P. 713–724. doi: 10.1007/978-3-642-02498-6_59

78. Ломаков С.Ю. Объёмы маммографических исследований в современных условиях проведения профилактических мероприятий // Профилактическая медицина. 2020. Т. 23, № 4. С. 41–44. EDN: OUUINQ doi: 10.17116/profmed20202304141

79. Roseman D.A., Hwang S.J., Manders E.S., et al. Renal artery calcium, cardiovascular risk factors, and indexes of renal function // Am J Cardiol. 2014. Vol. 113, N 1. P. 156–161. doi: 10.1016/j.amjcard.2013.09.036

AUTHORS' INFO

*** Adilya S. Nurkaeva;**
address: 45a Zaki Validi str. 450008, Ufa, Russia;
ORCID: 0009-0006-8621-5580;
eLibrary SPIN: 3307-5546;
e-mail: vkomissiya@inbox.ru

Yuri A. Trusov;
ORCID: 0000-0001-6407-3880;
eLibrary SPIN: 3203-5314;
e-mail: yu.a.trusov@samsmu.ru

Victoria S. Chupakhina;
ORCID: 0009-0003-8318-3673;
eLibrary SPIN: 4402-7476;
e-mail: chupalhina@bk.ru

Natalia A. Yakovenko;
ORCID: 0009-0005-6726-9623;
eLibrary SPIN: 4415-2236;
e-mail: tigris2011@yandex.ru

Irina V. Ablenina;
ORCID: 0009-0006-6222-9339;
eLibrary SPIN: 4123-3336;
e-mail: aninelba@gmail.com

Roksana F. Latypova;
ORCID: 0009-0004-5057-6451;
eLibrary SPIN: 3542-3376;
e-mail: roxevansss@gmail.com

Aleksandra P. Pitke;
ORCID: 0009-0002-1111-759X;
eLibrary SPIN: 3726-4213;
e-mail: pitkea00@gmail.com

Anastasiya A. Yazovskih;
ORCID: 0000-0002-3955-0830;
eLibrary SPIN: 3543-5323;
e-mail: anyaz.bgmu@yandex.ru

ОБ АВТОРАХ

*** Нуркаева Адиля Салаватовна;**
адрес: Россия 450008, Уфа, ул. ул. Заки Валиди, 45а;
ORCID: 0009-0006-8621-5580;
eLibrary SPIN: 3307-5546;
e-mail: vkomissiya@inbox.ru

Трусов Юрий Александрович;
ORCID: 0000-0001-6407-3880;
eLibrary SPIN: 3203-5314;
e-mail: yu.a.trusov@samsmu.ru

Чупахина Виктория Сергеевна;
ORCID: 0009-0003-8318-3673;
eLibrary SPIN: 4402-7476;
e-mail: chupalhina@bk.ru

Яковенко Наталья Александровна;
ORCID: 0009-0005-6726-9623;
eLibrary SPIN: 4415-2236;
e-mail: tigris2011@yandex.ru

Абленина Ирина Витальевна;
ORCID: 0009-0006-6222-9339;
eLibrary SPIN: 4123-3336;
e-mail: aninelba@gmail.com

Латыпова Роксана Фанилевна;
ORCID: 0009-0004-5057-6451;
eLibrary SPIN: 3542-3376;
e-mail: roxevansss@gmail.com

Питке Александра Петровна;
ORCID: 0009-0002-1111-759X;
eLibrary SPIN: 3726-4213;
e-mail: pitkea00@gmail.com

Язовских Анастасия Алексеевна;
ORCID: 0000-0002-3955-0830;
eLibrary SPIN: 3543-5323;
e-mail: anyaz.bgmu@yandex.ru

* Corresponding author / Автор, ответственный за переписку

Artem S. Ivanov;
ORCID: 0009-0000-3562-8293;
eLibrary SPIN: 4834-5324;
e-mail: artem.ivanov656@yandex.ru

Darya S. Bogatyreva;
ORCID: 0009-0004-5055-8819;
eLibrary SPIN: 3331-3421;
e-mail: diria1012@yandex.ru

Ulyana A. Popova;
ORCID: 0009-0002-7994-5631;
eLibrary SPIN: 3452-2543;
e-mail: ulyanka.popova.2000@gmail.com

Azat F. Yuzlekbaev;
ORCID: 0009-0002-8799-4732;
eLibrary SPIN: 4812-3213;
e-mail: ztl5@rambler.ru

Иванов Артём Сергеевич;
ORCID: 0009-0000-3562-8293;
eLibrary SPIN: 4834-5324;
e-mail: artem.ivanov656@yandex.ru

Богатырева Дарья Сергеевна;
ORCID: 0009-0004-5055-8819;
eLibrary SPIN: 3331-3421;
e-mail: diria1012@yandex.ru

Попова Ульяна Андреевна;
ORCID: 0009-0002-7994-5631;
eLibrary SPIN: 3452-2543;
e-mail: ulyanka.popova.2000@gmail.com

Юзлекбав Азат Флюрович;
ORCID: 0009-0002-8799-4732;
eLibrary SPIN: 4812-3213;
e-mail: ztl5@rambler.ru