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Use of artificial intelligence in the diagnosis of arterial calcification

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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.

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Применение искусственного интеллекта в диагностике кальцификации артерий

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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.

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人工智能在动脉钙化诊断中的应用

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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”，“искусственный интеллект”（人工智能）、“машинное обучение”（机器学习）、“кальцификация сосудов”（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。

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论证

在过去二十年中，俄罗斯联邦循环系统疾病的发病率持续上升，从2000年到2019年增加了2.047倍[1]。血管钙化过程包括钙盐在动脉壁沉积，导致血管壁重塑[2]。内膜钙化是局灶性的，与动脉粥样硬化有关，而中膜钙化是弥漫性的，是糖尿病、外周动脉疾病和慢性肾脏疾病等疾病的发病机理基础[3]。放射检查方法是诊断血管钙化的金标准[4]。然而，由于数据量的不断增加和缩短诊断时间的需要，工作效率不可避免地会下降[5]。这些情况促使人们寻找新的方面来提高仪器诊断人员的工作质量。

人工智能的积极发展和引入临床实践为专家解决这些问题提供了机会[6]。根据对现有文献数据的分析，迄今为止，人工智能已被用于5种血管钙化的X射线诊断：冠状动脉钙化、胸主动脉钙化、腹主动脉钙化、颈动脉钙化和乳内动脉钙化。

该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

作者在电子数据库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"、"искусственный интеллект"（人工智能）、"машинное обучение"（机器学习）、"кальцификация сосудов"（血管钙化）。检索时间从相关数据库建立之初至2023年7月。作者独立分析了文章的标题和摘要，然后提取了相关研究的全文。此外，还分析了相关研究的参考文献目录。

结果

研究被纳入综述的主要方法是比较临床医生和人工智能使用相同图像的诊断能力，然后评估准确率、速度和其他指标。

血管钙化的部位多种多样，这决定它们不同的预后价值。表1总结了不同部位血管钙化的预后价值。

冠状动脉钙化

弗雷明汉风险评分是心血管风险预测工具之一，该量表涉及年龄、性别和血压等风险因素的评估[7]。然而，一项为期7年的大型前瞻性研究报告称，通过电子计算机断层扫描（CT）诊断出的冠状动脉钙化可能会改善仅使用弗雷明汉风险评分得出的风险预测结果。M.H.Criqui等人在一项为期7.6年的随访研究中表明了，基于血管体积和密度的冠状动脉钙化严重程度评估具有良好的预后价值[8]。冠状动脉钙化体积与缺血性心脏病风险呈正相关，而冠状动脉钙化密度则呈负相关[8]。

钙化斑块密度和钙化面积的积分相乘即为冠状动脉钙化的程度。冠状动脉钙化总值是每个级别计算结果的总和。人们普遍认为，老年人是缺血性心脏病的主要风险人群[1]。然而，一项为期12.5年的研究表明了，即使冠状动脉钙化值较低，年龄在32至46岁之间的人罹患缺血性心脏病和死亡的风险也较高[9]。通过对这些研究结果的分析，我们可以得出结论，与冠状动脉钙化有关的信息在确定几乎所有年龄组的心血管事件风险方面都具有很高的预后价值。表2列出了冠状动脉钙化程度与不良心血管事件风险之间的关系。

表1。不同部位血管钙化的预后价值

血管钙化类型	预后价值
冠状动脉钙化	- 冠状动脉粥样硬化严重程度的标志； - 根据弗雷明汉风险评分对心血管风险的评估； - 缺血性心脏病预示因素； - 肿瘤化疗中心脏毒性的标志
胸主动脉钙化	- 缺血性心脏病风险增加的标志； - 脑梗塞增加风险的检测； - 栓塞风险的检测
腹主动脉钙化	- 是否存在阻塞性缺血性心脏病的检测； - 缺血性心脏病无症状病程的预测； - 充血性心力衰竭的标志
颈动脉钙化	- 头颈部血管动脉粥样硬化的标志； - 中风风险的检测； - 年轻人脑血管不良事件风险的预测
乳内动脉钙化	- 女生发生心血管事件风险的检测； - 与慢性肾脏疾病、糖尿病和骨疾病的关系

表2。冠状动脉钙化程度与不良心血管事件风险之间的关系

冠状动脉钙化评估	钙化风险
0	没有
1 - 10	低
11 - 100	中
101 - 400	高于中等水平
>401	高

胸主动脉钙化

众所周知，胸主动脉钙化广泛存在于高血压患者人群中[10]。此外，胸主动脉钙化与缺血性心脏病和死亡风险增加之间的关系也一再被揭示[10，11]。根据一项包括2618人的研究，Y.Itani等人发现了，胸主动脉钙化是评估脑梗塞风险的有效手段[12]。R.Lee等人在对有心血管手术适应症的患者进行的研究中发现了，对胸主动脉钙化状态的术前CT筛查 TAC可识别高风险区域，降低主动脉栓塞和中风的概率[13]。因此，胸主动脉钙化的程度不仅可以预测心血管事件风险，还有助于发现脑血管病变。

腹主动脉钙化

一项针对58名患者的研究发现了，使用CT评估的腹主动脉钙化评分与冠状动脉钙化的严重程度相关。反过来，如果没有腹主动脉钙化，则可以排除缺血性心脏病[14]。此外，研究还表明了，腹主动脉钙化可作为无症状缺血性心脏病的额外诊断工具，也是充血性心力衰竭发生的独立风险因素[15，16]。众所周知，腹主动脉钙化对骨系统具有重要的预后价值。Y.Z.Bagger等人进行了一项包括2662名绝经后健康女生的研究。研究结果表明了，腹主动脉钙化与股骨近端骨质疏松症的风险增加有关[17]。此外，P.Szulc等人的研究也证实了，腹主动脉钙化的存在与老年男生股骨骨折风险的增加相关[18]。

颈动脉钙化

颈动脉钙化是预测脑血管疾病的重要指标[19]。在不同种族群体中，颅内颈内动脉钙化是颅内高压的重要标志，与中风风险密切相关[19-21]。值得注意的是，一项包括约2000名患者的研究显示了，颅内颈内动脉钙化在年轻人中很常见。然而，尚不清楚年轻时的颅内颈内动脉是否与老年时发生的病理变化相似，从而是否能增加未来中风的风险[22]。

乳内动脉钙化

在一项包括213名患者的研究中，Z.Huang等人发现了，乳内动脉钙化与冠状动脉钙化和缺血性心脏病严重程度相关[23]。E.V.Bochkareva等人分析了4274例40-93岁女生的数字乳房X线图片。作者发现了，女生的年龄与乳内动脉钙化的存在之间存在统计学意义上的显著强相关性[24]。E.V.Bochkareva等人的其他研究清楚地表明了，乳内动脉钙化与慢性肾脏疾病、糖尿病、脑血管疾病和骨矿物质密度紊乱的发生有关[25-27]。遗憾的是，女性患者对心血管疾病的认识不足，而心血管疾病是威胁女性健康最严重的疾病之一[28]。因此，鉴于乳内动脉钙化评估的可用性及其反映女性心血管风险的诊断价值，仪器诊断医生应充分重视这一问题。

血管钙化的仪器诊断困难

对俄罗斯联邦2014-2019年放射诊断服务发展的分析表明了，医疗图像的数量每年都在增长，仪器诊断部门的医生在8小时的工作日内每3-4秒钟就要解读一次图像[29]。一项对40名仪器诊断专家工作前后身体状况的研究显示了，工作一天后，注意力明显不集中，眼疲劳症状加重[30]。据报道，75%的仪器诊断专家医疗缺陷诉讼与诊断错误有关[31]。

准确判断血管钙化程度是一项艰巨的任务。钙化灶的形状多变，受各种疾病的影响。例如，各种CT改良技术被用于诊断冠状动脉钙化[32]，但它们需要额外的设备，这增加医疗机构的经济负担，也增加患者的辐射负担（如果使用标准方法进行诊断，则可减少辐射负担）。此外，放射科医生并不总是对图像上反映的血管钙化进行评估，而血管钙化可被用于间接评估冠状动脉钙化，但金标准是具有确定检查区域的心脏同步CT[33，34]。

人工智能在动脉钙化评估中的作用

冠状动脉钙化

2007年，首次利用人工智能自动确定了冠状动脉钙化程度。为每个候选者开发了64个特征，然后采用近邻聚类法，这是一种用于自动对象分类或回归的度量算法，准确率达到73.8%[35]。随后几年，包括空间和几何方法在内的各种特征设计方法得到了积极探索[36-38]。由于在非对比CT图像中选择对象会造成技术上的困难，利用CT图像获得的信息与冠状动脉钙化检测进行配准已成为一种较为流行的方法[39-41]。为确定冠状动脉钙化，通常使用心电图同步来获取舒张期图像，然后通过“拼接”图像进行重建。使用支持向量机的算法灵敏度达到98.9%，预测值达到94.8%[42]。这种机器学习算法在2016年之前一直被积极使用，但由于需要人工控制，其应用存在一定的困难[42]。

为了进一步提高效率，人们选择了具有深度学习功能的人工神经网络作为主要方案[43]。起初，深度学习的性能并不令人满意，但通过对人工神经网络的不断改进，研究人员得以提高效率，实现准确、自动评分[44-51]。

B.D.de Vos等人在一项关于冠状动脉钙化测定的研究中发现了，使用深度学习获得的结果与人工计算的结果几乎相同，而Agatston指数（临床实践中钙计数的金标准CT方法）的测定不到0.3秒[52]。

U-Net算法是对人工神经网络的扩展，旨在利用更少的资源实现更高效的学习[53]。N.Gogin等人在研究中证实了基于U-Net架构的深度学习的有效性，其性能非常接近其他算法[46]。在86%的情况下，U-Net能

正确地对风险进行分类。值得注意的是，使用U-Net可以直接输入图像，而不会丢失像素信息[49]。

与无心电图CT相比，心电图同步CT的全球应用较低[54]。如果提高无心电图冠状动脉钙化信息的可靠性，就有可能减少CT检查的次数，从而降低经济成本和辐射暴露[55]。大量干扰和伪影的存在大大降低使用无心电图CT人工测定冠状动脉钙化的准确率[56]。

人工智能在使用无心电图CT诊断冠状动脉钙化方面发挥了重要作用。I.Isgum等人在10多年前就发现了，使用低剂量胸部CT进行Agatston评分，机器学习算法的准确率可达82.2%[57]。许多研究人员试图降低干扰和伪影水平，并减少非钙化成分（支架）对诊断的影响。他们开发的深度学习算法提高了低质量图像的价值[58,59]。Z.Sun等人证实了，深度学习算法将低剂量CT的信噪比提高了27.7%，由于消除了伪影，冠状动脉钙化检测的特异性提高了41%[60]。重要的是，无心电图CT解释正确率仅为70%；然而，使用人工智能和人工分析的结果之间的相关系数为0.923[56]。

在B.Yacoub等人进行的另一项研究显示了，在非对比胸部CT上检测冠状动脉钙化时，使用人工智能获得的灵敏度、特异性和曲线下面积（AUC）均优于人工结果。这表明，人工智能应用于无心电图CT的性能可能优于人工评估[34]。此外，一项研究在4个不同的中心证实了使用无心电图CT的人工智能的有效性。在所有样本中，均获得了较高的灵敏度和阳性预测值，从而提高了所得结果的质量[61]。应该指出的是，目前，基于无心电图CT的冠状动脉钙化诊断中应用人工智能是一种可靠的数据评估方法。

值得注意的是，研究人员已开始将人工智能功能应用于其他设备上的冠状动脉钙化诊断，例如分析胸片[62]。P.I.Kamel等人利用深度人工神经网络对胸片上的钙总量进行了分类，证明可以减少对一些患者的CT使用[63]。在这项研究中，检测冠状动脉钙化的前后位和侧位投影图像的AUC分别达到0.73和0.7。此外，一项研究提出了一种神经网络，可在数秒内分析有创冠状动脉造影时获得的图像，并以0.802的F1系数检测出冠状动脉钙化[64]。

胸主动脉钙化

与冠状动脉钙化相比，CT检测胸主动脉钙化的准确率与心脏收缩的强度无关[65]。例如，I.Isgum等人使用k-近邻法检测出97.9%的胸主动脉钙化，这与人工检查的结果相关[65]。近年来，深度学习的使用使得冠状动脉钙化和胸主动脉钙化的检测得以同时进行[66]。S.G.M.van Velzen等人也持类似观点，他们将所述方法应用于不同类型的CT扫描（包括冠状动脉钙检测的CT、低剂量胸部CT和正电子发射CT），类内相关系数从0.68到0.98不等[67]。值得注意的是，在一项使用卷积神经网络检测胸主动脉钙化的研究中，灵敏度达到了98.4%，不仅可以区分主动脉升段和降段以及主动脉弓的胸主动脉钙化，还可以确定风险的严重程度[68]。因此，使用人工智能自动评估冠状动脉钙化和胸主动脉钙化是放射科医生工作中不可或缺的一部分。

腹主动脉钙化

由于深度学习的进步，腹主动脉钙化自动检测的可能性已经实现，并在两项研究中得到证实[69，70]。双能X线吸收测量法是一种评估骨折风险的诊断方法。这种方法的使用越来越多，为自动评估腹主动脉钙化提供了可能，但由于技术上的困难，它并未用于常规腹主动脉钙化检测。S.Reid等人使用基于显象测密度法的卷积神经网络对腹主动脉钙化进行了分类，结果与人工获得的结果高度一致，Kappa评分为0.71[69]。值得注意的是，与双能X线吸收测量法相比，CT在主动脉钙化定量评估方面具有明显优势。P.M.Graffy等人利用腹部CT成功对9000多名患者进行了腹主动脉钙化自动检测，他们解释了原因是Mask Region-based Convolutional Neural Network的使用[70]。基于定量数据，该研究还评估了腹主动脉钙化的患病率，从而提高了人工智能的重要性。

总之，可以利用人工智能对腹主动脉钙化进行自动定量评估，但可用数据量非常有限。

颈动脉钙化

使用人工智能的CT可以诊断颈内动脉颅外和颅内部分的钙化[71，72，73]。G.Bortsova等人在研究中使用了4个结构类似于U-Net的深度学习网络，其颅内颈内动脉钙化检测的准确率高于人工评估，灵敏度为83.8%，预测值为88%[73]。人工评估颅内颈内动脉钙化需要仔细分析，容易出错，而且容易出现类似结构（如骨性钙化）的风险。因此，深度学习所表现出的高准确率就显得尤为重要。

磁共振成像可检测出颈动脉钙化与其他血管钙化之间最明显的差异[71]。在早期的研究中，使用磁共振成像检测钙化的准确率较低[71]。然而，SNAP（simultaneous non-contrast angiography and intraplaque hemorrhage）的使用提高了利用磁共振成像识别钙化的能力。使用SNAP时，所有信号均由反转脉冲反转，然后进行T1加权反转恢复，并使用双梯度回波进行质子密度加权控制扫描，这在颅内血管和颈椎成像方面效果极佳[74]。虽然SNAP能成功检测钙化，但它会受到运动伪影的影响，而且研究时间相对较长。使用Goal-SNAP和快速SNAP可以解决这一问题[75，76]。在本研究中，随机森林法等机器学习算法在钙化检测方面与人工神经网络相似，但深度学习在血管成分分割方面可能更有效，这需要进一步研究。

乳内动脉钙化

乳内动脉钙化可在乳房X线图片上看到，但钙化的表现形式千变万化。它们可以分叉、重叠、截断，强度也各不相同[77]。这种复杂性给人工乳内动脉钙化定量评估带来困难。

乳房摄影术是一种用于乳腺癌筛查的放射诊断方法，自2012年起被纳入预防性体检和健康检查的范围。根据俄罗斯联邦卫生部的规定，这种检查的频率每年都在增加[78]。

关于这个问题，很多学者都考虑过深度学习的应用。有人建议将乳房X线图片切成若干部分，由于直

表3。人工智能在5种血管钙化诊断中的应用结果比较

血管钙化类型	研究数量	射线摄影的应用	电子计算机断层扫描的应用	是否使用磁共振成像	深度学习的应用
冠状动脉钙化	大	有	有	没有	像素和端到端的深度学习与生成对抗网络相结合，可减少噪声和伪影，从而使冠状动脉钙化自动评估更加稳健，并可对结果进行可靠的评估
胸主动脉钙化	中等	没有	有	没有	深度学习可自动检测胸主动脉钙化和颈动脉钙化，从而评估不同主动脉部位的结果
腹主动脉钙化	小，需要更多研究	有	有	没有	掩码区域卷积神经网络等深度学习方法可使用双能X线吸收测定法和电子计算机断层扫描对腹主动脉钙化进行精确定量评估
颈动脉钙化	小，需要更多研究	没有	有	有	深度学习的效果似乎接近机器学习的效果，并优于人的能力，还能使用磁共振成像技术
乳内动脉钙化	中等	有	没有	没有	U-Net、SCU-Net、DU-Net和其他先进的深度学习系统有助于乳内动脉钙化检测

注：SCU-Net——简单上下文U网络；DU-Net——深度U网络。

接输入的数据量很大，这一点很有必要[53]。一个12层的卷积神经网络将乳内动脉钙化检测描述为一个二级问题[28]。虽然它能成功区分是否存在乳内动脉钙化，但其结果的定量评估不够准确[28]。此外，由于需要分别处理每个站点，数据分析和处理速度相当慢。随后，研究人员考虑到上述缺点，对卷积神经网络进行了改进，提出使用简单上下文U网络（SCU-Net）和深度U网络（DU-Net）[33，53]。SCU-Net是U-Net的简化版，它克服乳内动脉钙化只占图像的不到1%，从而产生大量数据、影响系统有效训练的挑战。DU-Net也避免这一问题，大大提高卷积神经网络的效率，准确率达到91.47%，灵敏度达到91.22%[53]。

总之，用于乳内动脉钙化自动检测的深度学习已经达到了很高的水平，但在这一领域还没有可靠的公开可用的统一数据集，因此需要在这一方向开展进一步的研究。

讨论

如上所述，人工智能可以通过进行预筛选和提高数据处理效率，促进和改善仪器诊断医生在血管钙化方面的工作。

人工智能应用于放射诊断的准确率与人工智能算法和图像特征有关。机器学习和深度学习算法的性能已取得显著进步，这有助于提高这些技术的诊断价值。随着成像技术的发展，图像质量不断提高，这对诊断性能产生了积极影响。人工智能能力与训练所需的高质量数据库相关联，这也有助于创建公开可用的数据库或测试平台。因此，未来工程师和临床医生应根据人工智能算法本身和图像质量，努力发展人工智能诊断能力。

值得注意的是，虽然人工智能在5种类型的血管钙化中显示出令人满意的效果，但它在肾动脉钙化等类型的钙化中具有潜在价值，而肾动脉钙化对动脉高血压和蛋白尿的预后价值已得到证实[79]。同时，专门针对腹主动脉钙化和颈动脉钙化的研究数量很少，这引起人们对其研究的更大兴趣。人工智能诊断各种类型血管钙化的效果比较见表3。

结论

人工智能在血管钙化诊断方面表现出色。除了提高准确率和效率外，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能够协助仪器诊断人员自动检测血管钙化的水平。未来，人工智能能力可能会促进放射学的有效发展。

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