Review Article

Artificial Intelligence in Carotid Ultrasonography: Current Status and Future Directions

Gustavo Paglioli Dannenhauer,[1] Simone Nascimento dos Santos,[2] Ana Claudia Gomes Pereira Petisco,[3] Claudia Maria Vilas Freire,[4] Ana Cristina Lopes Albricker,[5] Fanilda Souto Barros[6]

Clínica Biocor,[1] Caxias do Sul, RS – Brazil
Eccos Diagnóstico Cardiovascular Avançado,[2] Brasília, DF – Brazil
Instituto Dante Pazzanese de Cardiologia,[3] São Paulo, SP – Brazil
Universidade Federal de Minas Gerais (UFMG),[4] Belo Horizonte, MG – Brazil
IMEDE – Instituto de Ultrassonografia, CEU Diagnósticos, Faculdade de Medicina UNIBH,[5] Belo Horizonte, MG – Brazil
Instituto Fanilda Barros,[6] Vitória, ES – Brazil

Abstract

To review the current applications of artificial intelligence (AI) in carotid ultrasonography and its future perspectives. This narrative review was based on recent studies addressing machine learning, deep learning, radiomics, and integration with advanced ultrasound modalities, including contrast-enhanced ultrasound (CEUS), elastography, three-dimensional ultrasound, microvascular flow imaging (MFI), and ultrafast ultrasound. Carotid assessment has evolved from an approach focused primarily on the degree of luminal stenosis to a more comprehensive evaluation encompassing plaque burden, morphology, composition, and vulnerability. AI algorithms have been applied to automated plaque detection, image segmentation, plaque stability classification, radiomic feature extraction, and prediction of ischemic events. When combined with advanced imaging techniques, these models may improve reproducibility, reduce operator dependence, and reveal quantitative patterns that conventional visual assessment may not detect. Despite promising results, important challenges remain regarding image standardization, external validation, model explainability, and prospective clinical impacts. AI has the potential to transform carotid ultrasonography into a multiparametric tool for personalized medicine. Its clinical implementation will depend on robust validation, integration into clinical workflows, and demonstration of incremental value over conventional ultrasonography.

Introduction

Carotid atherosclerosis is an important marker of cardiovascular and cerebrovascular risk and has traditionally been assessed using ultrasonography with a predominant focus on the degree of luminal stenosis. This paradigm was established by landmark studies that supported therapeutic decision-making, particularly in symptomatic patients. However, advances in understanding of plaque biology have shown that stenosis alone does not fully account for the clinical risk, especially in asymptomatic individuals or those with non-obstructive lesions.[1–4]

Over the past decades, increasing evidence has demonstrated that the presence of plaque, its atherosclerotic burden, and morphological and compositional characteristics provide relevant prognostic information beyond that offered by traditional clinical risk scores. In contemporary cohorts, even small carotid plaques (including those associated with stenosis of less than 50%) have been associated with a progressive increase in the risk of atherosclerotic events, mainly when bilateral or accompanied by femoral artery involvement, reinforcing the concept of systemic and multivascular subclinical atherosclerosis.[2] In primary prevention, the quantification of plaque burden has shown greater predictive value than carotid intima-media thickness alone and has influenced clinical decision-making, including intensification of statin therapy.[5] These findings support the transition from a model focused exclusively on hemodynamics to a more comprehensive approach centered on plaque characterization and individualized risk stratification.[1–3,6,7]

Carotid ultrasonography plays a central role in this context, as it is a widely available imaging modality, free of ionizing radiation, and capable of providing information on anatomical, hemodynamic, and tissue characterization. In addition to plaque detection, carotid ultrasonography can assess maximum plaque thickness, echogenicity, surface irregularity, ulceration, atherosclerotic burden, and, through more recent techniques, intraplaque neovascularization, biomechanical properties, and three-dimensional plaque volume.[1,3] Clinical guidelines and consensus documents emphasize the role of carotid plaque as a biomarker of cardiovascular risk and the need to incorporate plaque characteristics beyond stenosis into clinical assessment.[3,4,8,9] Consistent with this concept, standardized proposals (e.g., Carotid Plaque-RADS) reflect the shift toward a more integrated evaluation of plaque vulnerability and stroke risk.[10,11]

Despite this potential, carotid ultrasonography remains partially limited by operator dependence, acquisition

Keywords

Carotid Arteries Ultrasonography; Artificial Intelligence; Atherosclerotic Plaque

Mailing Address: Gustavo Paglioli Dannenhauer •
Rua Sinimbu, 2211. Postal code: 95020-520. Caxias Do Sul, RS – Brazil
E-mail: gustavodannenhauer@gmail.com
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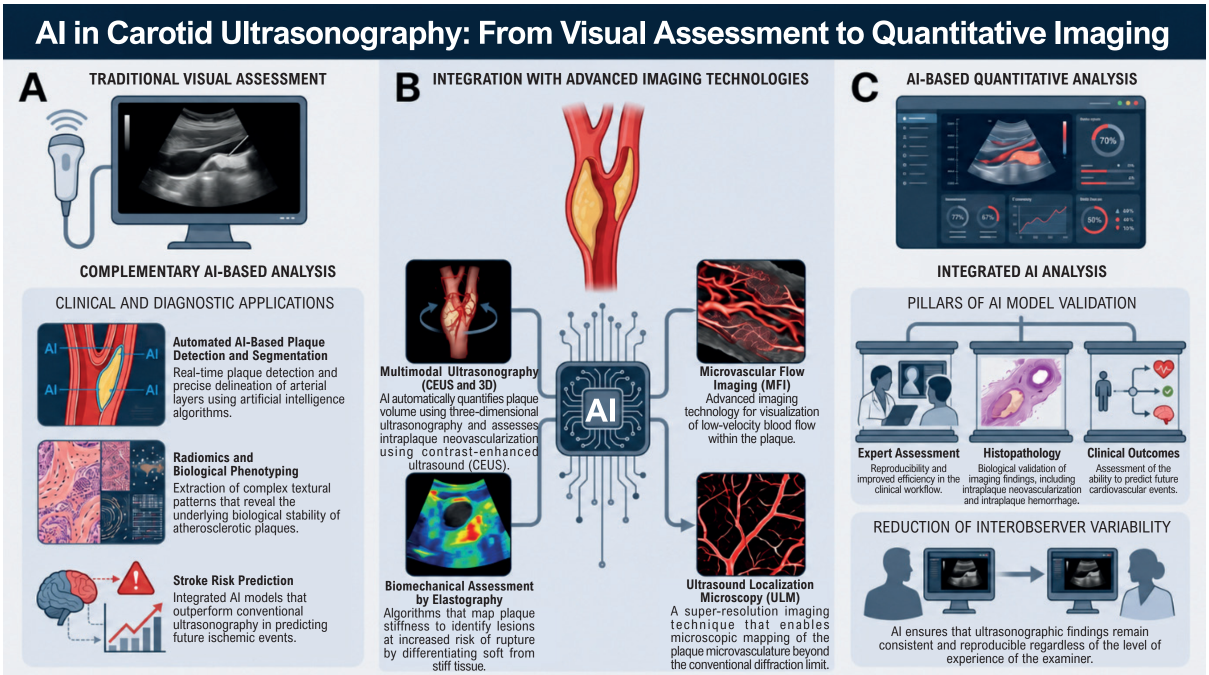
Central Illustration: Artificial Intelligence in Carotid Ultrasonography: Current Status and Future Directions



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variability, heterogeneity across ultrasound systems, and subjectivity in the interpretation of complex plaque phenotypes. Relevant features, such as a lipid-rich necrotic core, intraplaque hemorrhage, neovascularization, inflammation, and fibrous cap fragility, may be inferred from ultrasound findings but are not always detected or quantified reproducibly.[1,10,12] In this context, artificial intelligence (AI) has emerged as a promising tool.

The application of AI to carotid ultrasonography has expanded rapidly in recent years, encompassing automated plaque detection, lumen and vessel wall segmentation, plaque vulnerability classification, event prediction, and clinical workflow support. Models based on machine learning and deep learning have demonstrated the ability to extract textural and morphological patterns imperceptible to conventional visual inspection, with the potential to reduce interobserver variability, accelerate image analysis, and increase the prognostic value of carotid ultrasonography.[13–16] In parallel, advanced modalities (e.g., contrast-enhanced ultrasound [CEUS], elastography, microvascular flow imaging [MFI], three-dimensional ultrasound, and super-resolution ultrasound) provide novel imaging biomarkers that can be integrated with AI using multiparametric approaches.[17–21]

Therefore, this review discusses the current applications of AI in carotid ultrasonography and its future perspectives, with emphasis on plaque detection and quantification, vulnerability characterization, integration with advanced imaging modalities, and the potential impact on risk stratification and clinical practice (Central Illustration). Radiomics-based image feature extraction, a fundamental process in carotid ultrasonography (Figure A). AI-based multimodal integration and assessment of carotid plaque (Figure B). Types of endpoints in contemporary investigations using AI (Figure C).

Fundamentals of AI Applied to Carotid Ultrasonography

The application of AI to carotid ultrasonography relies on converting images into information that algorithms can analyze. In practical terms, this involves transforming a two-dimensional, dynamic, and operator-dependent examination into a structured dataset that supports tasks, such as plaque detection, anatomical segmentation, tissue characterization, and risk stratification for clinical decision-making.[13,14,22,23]

In general, AI applied to medical imaging can be understood at three main levels. The first is conventional machine learning, in which predefined features are extracted from the image and subsequently used by algorithms for classification or prediction. The second is deep learning, in which neural networks learn directly from image pixels and identify complex patterns without relying on manually selected variables. The third is the integration of both approaches, frequently combining automated segmentation, quantitative feature extraction, and composite clinical-imaging models.[13,14,23,24]

In carotid ultrasonography, this process begins with image acquisition, which provides the foundation for extracting input data, and no model can overcome severe limitations in input image quality. Inappropriate gain settings, excessive imaging depth, poor acoustic windows, marked acoustic shadowing, motion artifacts, limited standardization across ultrasound systems, or differences in acquisition protocols may substantially affect algorithm performance. This dependence explains why technical standardization and image harmonization have become central issues in the development of robust AI models.[23,25,26]

Following image acquisition, many AI processing workflows include segmentation, which is the automatic or semi-automatic identification of structures of interest, such as the lumen, intima-media complex, arterial wall, and atherosclerotic plaque. This step is critical because it defines the region from which quantitative information will be extracted. When segmentation is inaccurate, the model learns from noise, poorly defined borders, or nonrepresentative regions.[22,23,25-27]

Once the region of interest has been defined, AI can be applied in different ways. In conventional models, the image is converted into a set of quantitative features, including simple measurements (e.g., plaque thickness, plaque area, or mean echogenicity) and sophisticated descriptors of texture, heterogeneity, border characteristics, and intensity distribution. This is where radiomics plays a central role: it represents the transformation of an image into a rich matrix of quantitative variables (many of which are imperceptible to the human eye) that can be used to develop and train classification or predictive models.[22,23,26,28,29]

This approach is particularly relevant in carotid ultrasonography because plaque vulnerability depends not only on the degree of stenosis or overall visual appearance of the plaque but also on microstructural characteristics related to lipid composition, fibrosis, calcification, intraplaque hemorrhage, inflammation, and neovascularization. Radiomics can be understood as the bridge between conventional imaging and biological phenotyping of the lesion.[22,23,26,28]

In deep learning models, particularly convolutional neural networks, the network learns internal image representations through successive processing layers. Rather than requiring the investigator to define which features are relevant, the model independently identifies hierarchical patterns ranging from basic edges and contrast to complex shapes, textures, and spatial arrangements associated with plaque stability or vulnerability.[13,15,29-32]

The development of a reliable model also depends on rigorous methodological design. In simple terms, the available data must be divided into training, validation, and test sets. When a model excessively learns the specific characteristics of the training dataset and loses its ability to generalize, overfitting occurs, a problem that remains common in small, single-center, or highly homogeneous datasets.[16,23,26]

Another fundamental concept is external validation. A model that performs well using images acquired at a single center, with a single ultrasound system, and within a single population, may fail when applied to a different setting. Therefore, the true clinical value of AI is not determined solely by high areas under the receiver operating characteristic curve within the original dataset but by its ability to maintain performance across independent populations and real-world clinical environments.[13,16,26]

Performance metrics other than accuracy are equally relevant, including sensitivity, specificity, area under the receiver operating characteristic curve, calibration, and clinical utility. Models may accurately discriminate vulnerable plaques and still have limited clinical value if poorly calibrated, generate excessive false-positive results, or fail to influence clinical decision-making. Consequently, more mature studies integrate AI with clinical, laboratory, and hemodynamic variables rather than treating it as a standalone tool (i.e., multimodal AI).[29,31,33]

Model explainability represents another key challenge. In imaging exams that remain closely linked to expert visual interpretation, "black-box" models are likely to encounter resistance. Accordingly, interpretability strategies (e.g., attention maps and feature importance analysis) help identify which image regions or quantitative patterns contributed to a given classification.[14,26]

Current Applications of AI in Carotid Ultrasonography

Current applications of AI in carotid ultrasonography primarily focus on enhancing the ability of the exam to detect, quantify, and interpret signs of atherosclerosis in a more objective, rapid, and reproducible manner.[1,16,24]

One of the most intuitive applications of AI is the automated detection of atherosclerotic plaque. Recent deep learning models have demonstrated high performance in identifying plaques on B-mode ultrasound images, including in multicenter settings. For example, He et al.[13] demonstrated a deep learning algorithm capable of identifying and classifying carotid plaques according to plaque stability. At the population level, Omarov et al.[31] showed that automated plaque detection on carotid ultrasonography could support cardiovascular risk prediction and help identify genetic determinants of atherosclerosis. Moving closer to clinical implementation, real-time models based on architectures (e.g., You Only Look Once) have also been explored for instantaneous plaque recognition in ultrasound images and videos, suggesting potential applications in assisted screening and reduction of operator variability.[30]

However, plaque detection alone is only the first step. For quantitative image analysis, AI must accurately define the location of the lesion and its boundaries. This stage is critical because measurements, such as maximum plaque thickness, plaque area, and plaque burden, depend on reliable segmentation, which is inherently influenced by the quality of the pipeline used for model training. Moreover, most classification and quantitative modeling workflows require well-defined regions of interest.[22,25] Once the plaque has been identified and segmented, AI can be applied to quantify atherosclerotic burden. In this context, its main contribution is the automation of measurements that are more time-consuming or less reproducible when performed manually.

Following plaque identification, studies using AI pipelines have increasingly focused on distinguishing stable from vulnerable plaques, which is probably the area in which AI most directly attempts to translate pathophysiology into clinical decision-making. The objective is not simply to recognize the presence of a lesion but to infer whether it exhibits characteristics associated with increased risk of plaque rupture, embolization, and subsequent vascular events.[13–15]

Within this context, radiomics has assumed an important role as a clinical application of AI. Rather than relying solely on visual assessment or conventional morphological descriptors, radiomics transforms imaging data into a quantitative signature of plaque texture, heterogeneity, and internal organization. Song et al.[22] demonstrated that combining AI-assisted segmentation with ultrasound-based radiomics enabled an accurate discrimination between stable and vulnerable plaques. Jadoon et al.[28] extended this concept by extracting radiomic features from B-mode images and carotid wall radiofrequency signals. Complementarily, Zhao et al.[34] showed that radiomic approaches applied to the perivascular microenvironment may provide relevant information for identifying symptomatic plaques.

This application also extends to event prediction and risk stratification. Recent studies indicated that AI can integrate ultrasound variables with clinical data to predict the risk of cerebrovascular events, including ischemic stroke and clinical disease progression. Song et al.[22] and Jin et al.[32] demonstrated that ultrasound image-based models, particularly when integrated with CEUS, may improve the prediction of vulnerable plaques associated with increased risk of acute ischemic stroke. In patients with type 2 diabetes mellitus, a radiomics nomogram developed based on carotid ultrasonography to predict the risk of ischemic stroke achieved superior performance when the radiomics score was combined with clinical variables.[29] Chen et al.[35] also investigated predictive modeling based on ultrasound markers of intraplaque neovascularization, while Gao et al.[36] proposed an automated deep learning model for stroke risk stratification in patients with carotid plaques.

More recently, Jiang et al.[37] described the UltraBot system, a large-scale learning robotic platform that may represent the most emblematic example of the ongoing trend toward exam automation. This integrated system employs a robotic arm that reproduces probe movements, transducer pressure, and scanning angles, followed by fully autonomous image analysis and pattern recognition through an end-to-end model. In that study, the system achieved a plaque detection rate of 90%. On a smaller scale, real-time plaque recognition systems based on dynamic ultrasound videos also point toward future applications in remote assistance, telemedicine, and automated screening.[30]

Taken together, these applications reveal a clear pattern. The most advanced areas currently include plaque detection, segmentation, and classification in B-mode ultrasound images, along with substantial advances in CEUS, three-dimensional ultrasound, radiomics, and risk stratification. Nevertheless, the field remains characterized more by proof of capability than by full integration into routine clinical practice. In many situations, AI has already demonstrated performance comparable to or exceeding conventional visual assessments for specific tasks. The next step is to demonstrate that this superiority is consistent, generalizable, and clinically meaningful.[16,23,26]

Advanced Imaging Modalities and Their Integration with AI

Recent advances in carotid ultrasonography have substantially expanded the spectrum of information that can be extracted from the exam. Although conventional two-dimensional ultrasonography remains the foundation of carotid assessment, advanced modalities (e.g., CEUS, elastography, three-dimensional ultrasonography, MFI, and super-resolution techniques) provide more detailed insights into plaque composition, biomechanics, and microcirculation.[1,20,21,38]

Among these modalities, CEUS occupies a prominent position because it enables a more accurate characterization of the carotid plaque surface and facilitates the detection of biomarkers of plaque vulnerability, particularly intraplaque neovascularization, which has been associated with increased risk of cerebrovascular events. CEUS adds a functional dimension to conventional ultrasonography, and its findings have been associated with histopathological characteristics and the presence of vulnerable plaques.[39–44] The integration of AI with CEUS is promising because contrast imaging generates a large volume of dynamic information. Deep learning models can perform multitask segmentation and automated vulnerability assessment using CEUS images and videos.[17] The combination of features derived from B-mode ultrasonography and CEUS, analyzed using AI, improves prediction of vulnerable plaques associated with acute ischemic stroke.[17,32]

MFI represents the evolution of conventional Doppler techniques, which were developed to detect low-velocity blood flow in small-caliber vessels without the need for intravenous ultrasound contrast agents. MFI employs adaptive algorithms that separate true blood flow signals from tissue motion artifacts (clutter); thus, preserving low-velocity flow signals. The software also analyzes the spatial and temporal characteristics of ultrasound echoes to distinguish tissue motion artifacts from true blood flow. In carotid ultrasonography, this technology enables visualization of intraplaque microvascularization, improves lumen and vessel wall delineation, refines stenosis assessment, and facilitates the identification of plaque ulceration.[20,44] Studies have demonstrated excellent agreement between MFI and CEUS in detecting intraplaque neovascularization, as well as correlations with histopathological findings, reinforcing its potential as a noninvasive tool for assessing carotid plaque vulnerability.[45]

The most sophisticated example of this technological evolution is ultrasound localization microscopy, which enables assessing microvascular flow within human carotid plaques with histopathological correlation and at a spatial resolution substantially higher than that of conventional ultrasonography.[21]

Elastography, in turn, introduces a biomechanical dimension to plaque assessment. Strain elastography and shear-wave elastography infer the mechanical properties of the vessel wall and plaque based on the principle that lesions with different compositions exhibit distinct stiffness and deformation patterns.[19,46,47] Recent studies suggested that elastography differentiates vulnerable from stable plaques and is associated with clinical outcomes.[35,47,48] The application of AI in this field may be particularly valuable by integrating elasticity maps with morphological, textural, and clinical information.[46]

Three-dimensional ultrasonography adds another important dimension to carotid imaging. Its primary contribution is to provide a more accurate assessment of atherosclerotic burden, particularly through volumetric measurements. Unlike two-dimensional imaging, which captures only selected cross-sections of the lesion, three-dimensional ultrasonography enables plaque volume reconstruction, improved surface characterization, and more robust longitudinal monitoring.[18,49,50] Integrating three-dimensional ultrasonography with AI is particularly well-suited because manual volumetric analysis is labor-intensive and highly examiner-dependent.[49–51]

The above-mentioned imaging modalities clearly indicate that the future of carotid ultrasonography is multiparametric. Two-dimensional ultrasonography provides basic morphological information, CEUS depicts neovascularization, elastography characterizes biomechanical properties, MFI evaluates blood flow in vessels with very low flow velocities, three-dimensional ultrasonography quantifies plaque burden and volume, and super-resolution techniques bring imaging closer to histological resolution.[1,20,21]

Methodological Limitations and Challenges for Clinical Implementation

Although the literature on AI applied to carotid ultrasonography has expanded rapidly, its interpretation requires careful methodological consideration. Overall, studies differ not only in algorithm architecture, sample size, and imaging modality but, more importantly, in the type of reference standard (i.e., ground truth) used to train and validate AI models. In practice, these reference standards generally fall into three main categories: expert assessment, histopathology, and clinical outcomes.[23,26]

Expert-based reference standards are currently the most commonly used. This strategy offers the advantages of feasibility, scalability, and close alignment with routine clinical practice; however, it inherits the very human variability that AI is intended to reduce. In other words, an algorithm may become highly effective at reproducing the interpretative pattern of a specific expert or institution without necessarily capturing the underlying biological characteristics of the lesion. This helps explain why many studies report excellent internal performance while still raising concerns regarding generalizability and external validity.[23,25,26] Available methodological reviews reinforce this concern. Although many models, particularly radiomics-based models, achieve high area under the curve (AUC) values, their overall methodological quality remains limited, with a high global risk of bias and weaknesses related to feature selection, validation, and reproducibility.[23,26]

Histopathology-based reference standards are more methodologically robust because they anchor imaging findings to objective biological outcomes. In carotid plaque studies, histopathological analysis enables validating features, such as intraplaque neovascularization, lipid-rich necrotic core, intraplaque hemorrhage, inflammation, and tissue composition. Studies involving CEUS, elastography, three-dimensional ultrasonography, and ultrasound localization microscopy are strengthened when imaging findings are correlated with carotid endarterectomy specimens.[21,43,50] Nevertheless, histopathology reference standards also have limitations: they are derived from highly selected populations, which generally comprise patients with more advanced disease and surgical indications; thus, limiting their representativeness across the broader spectrum of outpatient clinical practice.

The third category, and possibly the most important for real-world implementation, is the use of clinical outcomes as the reference standard. In this context, the value of AI is no longer measured solely by the agreement with imaging findings or histopathology but rather by its ability to predict cardiovascular events, disease progression, or the need for intervention. Although this approach is the most clinically relevant, it is also the most challenging because it requires larger cohorts, longer follow-up periods, careful control of bias, and more robust predictive models.

These different levels of reference standards illustrate that the clinical implementation of AI depends on algorithmic accuracy and the specific clinical question the model is designed to answer. An algorithm trained to reproduce manual plaque contours generated by an expert addresses a fundamentally different problem from one validated against histopathology, and both differ from a system that predicts future clinical events. For AI to advance consistently in carotid ultrasonography, these levels must be integrated into a translational hierarchy: first, accurate segmentation and technical robustness; next, biological validation; and last, demonstration of prognostic value and impact on routine clinical decision-making.[2,5,23,26]

In summary, the current challenge is not the development of increasingly sophisticated algorithms but the design of studies based on reference standards that are clearly defined, clinically relevant, and methodologically defensible. Without this foundation, there is a risk of producing technically impressive algorithms that are trained to reproduce imperfect representations of the disease. The successful clinical implementation of AI in carotid ultrasonography will depend less on performance within isolated datasets and more on its ability to integrate imaging, biology, and clinical outcomes into validated, reproducible, and clinically useful models.[21,23,26]

Future Perspectives

Future perspectives for AI in carotid ultrasonography point less toward replacing the specialist and more toward establishing a progressively quantitative, multiparametric, and risk-oriented imaging ecosystem. The field appears to be moving toward the convergence of automated image acquisition, robust segmentation, advanced plaque phenotyping, and integration with clinical outcomes.[1,20,21]

One of the most promising directions is the evolution of AI from retrospective classification systems to multimodal models. Rather than analyzing B-mode images alone, future algorithms are expected to integrate information on plaque texture, plaque volume, neovascularization assessed by CEUS, MFI, biomechanical properties derived from elastography, local hemodynamics, and clinical and laboratory variables. Recent studies suggested that predictive performance improves when multiple sources of information are combined, reinforcing the concept that plaque vulnerability is unlikely to be adequately captured by a single biomarker.[21,32,33,48]

Another important area of development is the automation of the exam. The emergence of robotic systems and AI-assisted image acquisition suggests that operator variability may be reduced during image acquisition.[37] In the medium term, AI may support image interpretation and real-time guidance of the examiner, automatic standardization of imaging planes, and selection of the most informative frames for subsequent analysis.[1,3]

Another advance is the progress toward super-resolution imaging and direct quantification of plaque microcirculation. Ultrasound localization microscopy currently represents the clearest example of this frontier, enabling visualization and quantification of plaque neovessels at a spatial resolution substantially higher than that of conventional ultrasonography.[21] Similarly, contrast-free MFI techniques may evolve from promising but heterogeneous technologies to more standardized imaging biomarkers, particularly when combined with AI algorithms for automated quantification and classification.[20,21]

Conclusion

AI is repositioning carotid ultrasonography from a predominantly anatomical and operator-dependent exam to an increasingly quantitative, integrated, and risk-oriented imaging modality.

The true contribution of AI lies within this context rather than in competition with clinical expertise. Far from diminishing the role of the specialist, AI strengthens it by providing tools that improve the precision, efficiency, and speed of image interpretation while establishing carotid ultrasonography as a valuable modality for individualized risk assessment and a more personalized approach to vascular disease.

Author Contributions

Conception and design of the research, acquisition of data, analysis and interpretation of the data, statistical analysis, writing of the manuscript and critical revision of the manuscript for intellectual content: Dannenhauer G, Santos SN, Petisco ACGP, Freire CMV, Albricker ACL, Barros FS.

Potential Conflict of Interest

The author declares no relevant conflicts of interest.

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This study is not associated with any graduate-level academic program.

Ethics Approval and Consent to Participate

This article does not contain studies involving human participants or animals conducted by any of the authors.

Use of Artificial Intelligence

During the preparation of this work, the author(s) used ChatGPT for searching bibliographic references and assembling the study's central figure. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

Availability of Research Data

The data underlying this study are contained within the manuscript.

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