REVIEW ARTICLE

ADVANCING VASCULAR SURGERY: THE ROLE OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN MANAGING CAROTID STENOSIS

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Abstract

Introduction: *Cardiovascular diseases affect 17.7 million people annually, worldwide. Carotid degenerative disease, commonly described as atherosclerotic plaque accumulation, significantly contributes to this, posing a risk for cerebrovascular events and ischemic strokes. With carotid stenosis (CS) being a primary concern, accurate diagnosis, clinical staging, and timely surgical interventions, such as carotid endarterectomy (CEA), are crucial. This review explores the impact of Artificial Intelligence (AI) and Machine Learning (ML) in improving diagnosis, risk stratification, and management of CS.*

Methods: *A comprehensive literature review was conducted using PubMed and SCOPUS, focusing on AI and ML applications in diagnosing and managing extracranial CS. English language publications from the past two decades were reviewed, including cross-referenced scientific articles.*

Results: *Recent advancements in AI-enhanced imaging techniques, particularly in deep learning, have significantly improved diagnostic accuracy in identifying carotid plaque vulnerability and symptomatic plaques. Integration of clinical risk factors with AI systems has further enhanced precision. Additionally, ML models have shown promising results in identifying culprit arteries in patients with previous cerebrovascular events. These advancements hold immense potential for improving CS diagnosis and classification, leading to better patient management.*

Conclusion: *Integrating AI and ML into vascular surgery, particularly in managing CS, marks a transformative advancement. These technologies have significantly improved diagnostic accuracy and risk assessment, paving the way for more personalized and safer patient care. Despite clinical validation and data privacy challenges, AI and ML have immense potential for enhancing clinical decision-making in vascular surgery, marking a pivotal phase in the field's evolution.*

Keywords: *Carotid stenosis; carotid endarterectomy; perioperative stroke.*

INTRODUCTION

Annually, around 17.7 million people are affected by cardiovascular (CV) diseases, including myocardial infarction (MI) and strokes, with atherosclerosis being the major contributor to these events.(1)

Carotid disease, which involves the accumulation of atherosclerotic plaques, is a significant risk factor for cerebrovascular events and ischemic strokes. It is estimated that carotid disease affects roughly 27.6% of individuals between the ages of 30 and 90, globally.(2)

For high-risk stroke patients with carotid stenosis (CS), carotid endarterectomy (CEA) is the preferred treatment, whether symptomatic or asymptomatic, while transfemoral carotid stenting (CAS) is considered as an alternative in selected cases.(3) However, it's important to note that every surgery involves inherent perioperative risks. Surgical interventions such as CEA often involve patients with multiple comorbidities, which categorizes these procedures as high-risk interventions.[4] Despite advancements in surgical techniques and perioperative care, certain patients undergoing CEA under regional anesthesia experience intraoperative neurologic deficits (IND) during carotid artery cross-clamping. These deficits, indicative of critical cerebral perfusion impairments, significantly increase patient management complexity and are associated with increased postoperative complications, including stroke.[5]

The Society for Vascular Surgery sets a goal for the perioperative stroke/death rate to be under 6% for symptomatic patients and under 3% for asymptomatic patients, underlining the need for accurate prediction of postoperative outcomes to aid in clinical decision-making.[6, 7]

Predictors such as increased red cell distribution width coefficient of variation, age, obesity, and specific degrees of ipsilateral and contralateral carotid stenosis have been identified as relevant factors for predicting IND during CEA.[5] Harnessing the potential of artificial intelligence (AI) to improve risk stratification and clinical outcomes in CS management is crucial with the expanding amount of data and continual technological progress.

The AI into CV disease management has marked a significant advancement. [8] Machine learning (ML), a prominent branch of AI, allows computer systems to learn from data, identify patterns, and predict outcomes without explicit programming. ML offers a more advanced and nuanced approach, condensing vast data volumes to meaningful insights and overcoming some limitations of conventional statistical models, mainly based on inference and probability.[7, 8]

With its heavy reliance on medical imaging and significant advancements due to the endovascular revolution, vascular surgery is an ideal area for sophisticated ML integration.[9]

AI is increasingly recognized for its potential to enhance diagnostic accuracy, optimize patient selection for surgical procedures, including predicting IND and predict critical long-term outcomes, such as strokes. [8, 10]

This review focuses on applying AI and ML models for predicting CS patients, risk stratification post-CEA/CAS adverse events, and identifying the main predictors. The increasing relevance of AI in the medical field, particularly for diagnostic and prognostic purposes in CS, underpins this review. [7] Additionally, it will highlight recent studies and expected advancements in this rapidly evolving field of medicine.

METHODS

A comprehensive literature review was carried out to collate data from relevant studies in patients with extracranial stenosis. The search was performed resorting to PubMed and SCOPUS on november 2023 with the keywords / MESH terms "carotid stenosis" and "carotid endarterectomy" in combination with the terms "artificial intelligence" and "machine learning". For this study, the authors focused on publications in the past decade, between january 2014 and march 2024, using English language publications. Additional articles of scientific interest for this non-systematic review were included by cross-referencing.

RESULTS

Carotid stenosis

Due to distinctive blood flow patterns, supra-aortic vessels are susceptible to atherosclerosis, particularly at their bifurcation points. The plaques formed in these arteries are typically composed of lipids and inflammatory cells enclosed by a fibrous capsule. [11] When these plaques are present in the carotid artery, they can cause blockages or, occasionally, rupture, leading to clots. Such events are frequently implicated in ischemic strokes, which are often due to emboli originating from these atherosclerotic plaques. [11, 12] Thrombotic plaques are more commonly observed in individuals who have suffered strokes (66.9%), compared to those with transient ischemic attacks (TIAs, 36.1%) or in asymptomatic individuals (26.8%). Initially, the embolization caused by these plaques may lead to TIAs.[11]

A comprehensive analysis of patient data indicates that surgical intervention considerably reduces the risk in cases of severe CS (70% to 99%) but provides limited benefits for moderate stenosis (50% to 69%). It has been suggested that centers using the European Carotid Surgery Trial (ECST) or the common carotid method adapt their recommendations to suggest surgery for severe stenosis (82% to 99%) and implement individualized risk assessments for moderate stenosis (65% to 81%).[13]

In a study focusing on symptomatic patients with suspected internal carotid (ICA) stenosis, comparing contrast-enhanced magnetic resonance angiography (CEMRA) with digital subtraction angiography (DSA), CEMRA was found to slightly overestimate stenosis severity, especially when using the ECST method. This result contrasted with the North American Symptomatic Carotid Endarterectomy Trial (NASCET) method, where CEMRA showed lower sensitivity in detecting severe stenosis.[13]

Understanding CS, particularly its development and its risk for ischemic strokes, is crucial in vascular field. The use of surgical interventions like CEA, guided by reliable diagnostic methods and risk stratification techniques such as NASCET and ECST, plays a pivotal role in preventing stroke in patients with significant stenosis. However, the challenge lies in accurately diagnosing the severity of stenosis, as techniques like CEMRA may have limitations, notably in overestimating stenosis compared to DSA, particularly with the ECST method.

AI in unstable carotid plaque detection

In recent years, there has been increasing evidence suggesting that plaque characteristics correlate with neurological adverse events, leading to the concept of vulnerable plaques. Neovascularization within plaques has emerged as a significant predictor of plaque rupture. [14]

Carotid plaques, with their varied components formed during different stages of plaque development, present a diagnostic challenge due to image noise and lesion complexity. [15, 16]

Recent advancements in AI, namely in deep learning (DL), have greatly improved medical imaging techniques. In a study by Guang et al., a DL system applied to ultrasound (US) imaging for identifying carotid plaque vulnerability achieved area under the curve (AUC) scores of 0.85 and 0.87 in training and validation, respectively. This result surpassed experienced radiologists' performance, who achieved scores of 0.69 and 0.66, underscoring DL's potential in enhancing diagnostic precision. [14]

Similarly, Huang et al. developed an advanced model combining US-based radiomics (plaque size, length, thickness, plaque echogenicity, and contrast enhancement) and clinical features (hypertension [HT], high-sensitivity C-reactive protein exceeding the upper normal limit, diabetes, smoking, and clinical symptoms such as anterior circulation ischemic stroke in the carotid region, classic TIA, amaurosis fugax or retinal artery occlusion ipsilateral to the carotid artery plaque), significantly improving the detection of symptomatic carotid plaques. This model achieved high predictive accuracy, with AUC scores of 0.93 and 0.92 in training and testing, outperforming traditional US and clinical models, which scored 0.723 and 0.580, respectively, demonstrating the effectiveness of AI-enhanced methods.[17]

Further enhancing the capabilities of AI in vascular imaging, a study showed that an ML system integrating carotid US images with traditional clinical risk factors: age, glycated hemoglobin (HbA1c), plaque score (PS), carotid intima-media thickness average (cIMTave), low-density lipoprotein cholesterol (LDL-c), fasting blood sugar (FBS), HT, triglyceride (TG), total cholesterol/high-density lipoprotein-cholesterol (TC/HDL-c) ratio, smoking, square harmonic of cIMTave, HDL-c, family history (FH), TC, cIMTave 10yr, variability of carotid intima-media thickness (cIMT) 10yr, difference between average lumen diameter and maximum cIMT, and total plaque pixels) reached an AUC of 0.80 ($p<0.0001$). This result was an 18% improvement over the conventional system using only clinical risk factors (age, HbA1c, LDL-c, FBS, HT, TG, smoking, FH, and TC/HDL ratio). The study highlighted HbA1c, PS, and cIMTave as the top three predictive features and the model's ability to assess CV and stroke risks with high precision and clinical relevance. However, the study's focus on a Japanese cohort may limit the wider applicability of these findings.[1]

Additionally, other research efforts involved analyzing duplex ultrasonography and transcranial doppler data from 538 subjects. This study compared the performance of the random forest (RF) model with logistic regression (LR) for stenosis classification. The RF model showed superior accuracy, sensitivity, and specificity, with AUC values between 0.99 and 1.00. Peak systolic velocity was a key predictor in the ICA.[18]

AI's application extends beyond the US to other imaging modalities. Le et al. explored the use of radiomic features from carotid computed tomography angiography (CTA) to identify culprit arteries in patients with previous cerebrovascular events (TIA or stroke). ElasticNet model achieved an AUC of 0.73, indicating a promising level of accuracy in identifying the culprit and non-culprit arteries, which could significantly aid in stroke prediction. The three most relevant predictors were grey level dependence matrix: dependence variance, grey level size zone matrix: grey level non-uniformity, and grey level run length matrix features: long run high grey level emphasis.[19]

Further illustrating the versatility of ML in this field, Xia H et al. conducted a study where they developed five ML models to predict ischemic cerebrovascular events in patients with mild CS (30–50%). This study, utilizing radiomics and clinical data from CTA, involved 179 patients and identified the RF model as the most effective, achieving an AUC of 0.879. The most important predictive features were 3D diameter, LDL, and uric acid. The study, however, faced limitations such as small sample size and potential bias due to manual image segmentation.[20]

These AI and ML approaches in vascular imaging, especially in carotid plaque analysis, significantly advance personalized patient care. Enhancing diagnostic precision and risk assessment revolutionizes the management of extracranial atherosclerotic conditions.

Table 1 highlights the main characteristics of the reviewed articles, emphasizing the clinical application and type of the prediction models.

AI applied to carotid stenosis screening

Asymptomatic carotid stenosis (ACS) is closely associated with the incidence of severe cerebrovascular diseases, which can often be discovered incidentally through medical imaging. However, medical imaging is not recommended in asymptomatic patients without clinical manifestations or risk factors of atherosclerosis.[21, 22] Detecting CS in asymptomatic patients is key for predicting and preventing serious CV events such as MI, strokes, and CV deaths. [21, 22]

Different studies have been done to evaluate the potential of AI in ACS. Table 2 provides an overview of studies investigating AI's application in the ACS assessment. In a study by Yu et al., ML was used to screen 2732 asymptomatic adults for CS. They developed five models, and the multilayer perceptron model, which emerged as the most accurate (0.748), identified CS in 942 individuals (34.5%) with an AUC of 0.766, followed by Extreme Gradient Boosting (XGBoost) ML algorithm which achieved an accuracy of 0.741 and an AUC of 0.763, highlighting age, blood pressure (BP), homocysteine, and HDL-c as key risk factors.[22]

Yin et al. demonstrated that the RF algorithm could be used to identify key risk factors associated with ACS. However, the model can only be applied to high-risk individuals with stroke. The model achieved a high level of accuracy in detecting ACS, with an AUC of 0.927 in the training dataset and 0.888 in the testing dataset. The identified risk factors included a FH of dyslipidemia, elevated LDL-c, reduced HDL cholesterol, aging, and low body mass index (BMI).[23] In another study analyzing 18,441 participants, 35.5% were diagnosed with asymptomatic CS. Six AI models were tested, with the LR model being the most effective, achieving an AUC of 0.809, 74.7% accuracy, and an F1 Score of 59.9%. The study identified age, systolic BP, glucose, HDL cholesterol, and platelet count as significant risk factors for CS.[24] For instance, Poorthuis et al. performed a systematic review where it aimed to validate prediction models for ACS in a large external population. Six prediction models were identified; among them, the LR model developed by Weerd et al. demonstrated the highest predictive performance. The risk factors considered in the best-performing model included age, sex, smoking, HT, hypercholesterolemia, diabetes mellitus, and medical history of MI, stroke, or TIA. The model exhibited an AUC of 0.749 for predicting ≥50% ACS and 0.779 for predicting ≥70% ACS. Targeted screening of individuals in the highest-risk decile successfully identified 35% of cases with ≥50% ACS and 42% of cases with ≥70% ACS.[25]

Another study implemented five ML models, where RF had the highest predictive value and achieved an impressive 82% accuracy and a 90% AUC based on a dataset of 881 cases for diagnosing of patients with ACS. The most influential factors included aneurysm disease, BMI, weight, height, and high lipid levels.[21]

ML-based predictive models are valuable for healthcare providers in identifying CS in asymptomatic individuals, even those without usual risk factors. These AI tools enhance risk assessment accuracy, aiding in early measures to prevent CV and cerebrovascular events in asymptomatic adults. Nonetheless, it is important to note that the omission of certain lifestyle factors in some models may limit their effectiveness, and their inclusion could refine the predictive accuracy.

Artificial intelligence in risk stratification

The field of AI research focusing on risk stratification plays a crucial role in identifying patients with chronic vascular diseases who are prone to complications. This approach allows for early intervention to prevent potential issues and mitigate the risk of serious post-operative complications.[8]

Currently, there is a lack of effective tools for predicting outcomes in CEA patients, with existing models exhibiting methodological limitations and suboptimal performance, with AUC values ranging from 0.58 to 0.74. These results underscore the need to develop better surgical risk prediction tools for patients undergoing CEA.[6, 26] Table 3 provides an overview of studies focusing on risk stratification.

Recent studies have incorporated the Modified Integrative Cardiac Assessment (MICA) risk score, leveraging decision trees, to enhance predictive accuracy in CEA. A cohort study involving 194 patients analyzed variables such as the MICA risk score, BMI, age, sex, presence of chronic kidney disease, and degree of CS. Originally developed for cardiac risk assessment, the MICA score demonstrated substantial predictive capability for IND, achieving an AUC of 0.656 for perioperative stroke prediction. Patients with higher contralateral stenosis had 29% increased odds of IND, while higher ipsilateral stenosis exhibited a protective effect against IND occurrence. Obesity, defined by a BMI > 30 kg/m^2, emerged as a prominent independent risk factor, quadrupling the likelihood of IND during CEA. These findings underscore the role of AI in refining patient stratification and preoperative risk management strategies, thereby improving surgical outcomes and enhancing patient safety.[10]

For instance, Bai P et al. used the XGBoost to predict ischemic events such as cerebral infarction and MI post-CEA in CS patients. Among 443 patients, there were 6 cases of cerebral infarction and 10 of MI. Mean arterial pressure during occlusion, BMI, mean arterial pressure after the operation, the standard deviation of systolic pressure during occlusion, diastolic pressure during occlusion, mean arterial pressure entering the room, systolic pressure during occlusion, and age were identified as the variables affecting the risk of ischemic events. However, limitations like small sample size affected the model's stability. This study underlines the significance of BP in forecasting postoperative risks and suggests the influence of other factors like antiplatelet use and microemboli detachment.[27]

Matsuo K et al. used AI, particularly the XGBoost model, to predict 30-day ischemic stroke risk post-CEA or CAS in 170 patients, considering 17 clinical factors. The study found that the XGBoost model performed best, with an accuracy of 86.2%, but had a lower sensitivity of 31.9%. Key predictors by order included ICA peak systolic velocity, serum LDL-c, and the type of procedure (CEA or CAS). This study provides a useful tool for assessing stroke risk post-procedure, determining if the patient is suitable for CEA or CAS based on the calculated risk, suggesting potential enhancements with larger datasets and more factors.[28]

Tan J et al. used gradient boosted regression trees (GBRT) to predict early-phase post-operative hypertension (EPOH) after CEA. Patients with EPOH had higher incidence of postoperative cerebral hyperperfusion syndrome (7.5%), and higher incidence of cerebral hemorrhage (3.8%). Analyzing 406 CEA procedures, their GBRT model showed a promising average AUC of 0.77 but a lower specificity of 0.52, possibly due to the small sample size. Key factors contributing to EPOH are identified, including intraoperative BP peaks, deceleration time of the E-wave velocity, propofol, ipsilateral severity of stenosis, cardiac index, fentanyl, and ephedrine. Despite limitations such as its retrospective design and reliance on single-center data, the study is valuable for early identification of high-risk patients, potentially enhancing patient care and resource use.[29]

Other investigators developed ML models to predict 30-day major adverse CV events (stroke, MI, or death) following CEA. Six ML models were developed. The XGBoost model showed the highest accuracy, with an AUC of 0.91, significantly outperforming the traditional LR model, AUC of 0.62. The key ten predictors were symptomatic CS, history of congestive heart failure (CHF), American Society of Anesthesiologists (ASA) class, functional status, transfer from another hospital, preoperative dialysis, physiologic high-risk factor, revision CEA, anatomic high-risk factor, and urgency of surgery.[26]

The utilization of ML in predicting postoperative outcomes for CEA represents a significant advancement with profound implications for the future of vascular surgery. It can lead to more informed clinical decision-making, potentially improving patient outcomes and reducing healthcare costs.

Long-term event prediction

With an established understanding of the challenges posed by CS and the associated complications, the need for more accurate predictive tools becomes evident.

By having the potential to outperform existing tools and the ability to accommodate a wide range of clinical variables, ML algorithms open doors to more accurate and automated perioperative risk mitigation strategies.[6]

Li B et al. developed six ML models to predict stroke or death events within one year post CEA surgery. Among 166369 patients, 7749 patients (4.7%) developed stroke or death. XGBoost model exhibited the highest performance, with an AUC exceeding 0.90. The top 10 predictors included eight preoperative features (dialysis, prior major amputation, preoperative living status, existing CHF, symptomatic CS, preoperative hemoglobin, existing HT, and prior ipsilateral CEA). Additionally, one intraoperative feature (surgical re-exploration) and one postoperative feature (in-hospital MI) were significant predictors. Compared to existing models, these ML models demonstrated superior performance, making them a valuable tool for guiding the treatment of CS patients.[6]

In another study, DeMartino et al. used the vascular quality initiative database to develop LR models predicting 30-day stroke and 1-year mortality for asymptomatic patients undergoing CEA. The analysis included a total of 31,939 patients for the stroke analysis and 23,512 patients for the mortality analysis. The developed models demonstrated promising performance, with an AUC of 0.67 for the 30-day stroke model and 0.76 for the 1-year mortality model.

Ten key predictive factors were identified for each model. For the 30-day stroke model, factors such as contralateral carotid occlusive disease, female sex, ASA class, prior aneurysm repair, preoperative hemoglobin level, coronary artery disease, HT, and estimated glomerular filtration rate class were associated with increased odds of stroke, while the use of antiplatelet agents and more severe ipsilateral stenosis were linked to lower odds of stroke. Similarly, for the 1-year mortality model, factors including anemia, ASA class, age, smoking status, contralateral carotid occlusive disease, severity of renal disease, chronic obstructive pulmonary disease, CHF, and diabetes were associated with higher odds of mortality, while a normal result on stress testing was associated with lower odds of mortality.[30]

This underscores the importance of thorough preoperative risk assessment and optimization in patient management before CEA.

Future Developments and Ongoing Research

The integration of AI into the field of CS and vascular surgery marks a significant advancement in medical science. Originating in 1956, AI has become a crucial element in various daily activities, notably in medicine and surgery, including in vascular diagnostics, risk stratification, and outcome prediction in procedures like CEA.[31]

AI tools such as ML, natural language processing, and deep neural networks are increasingly being utilized to detect diseases such as abdominal aortic aneurysms, peripheral arterial disease and atherosclerotic cardiovascular disease, which often go underdiagnosed. These technologies not only improve disease detection and risk assessment but also enhance data collection and quantitative measures across large datasets by analyzing medical records. [32]

In vascular surgery, accurate patient selection is crucial for optimizing clinical outcomes and minimizing complications. AI and ML play pivotal roles in this endeavor, particularly in risk assessment and personalized decision-making. AI-driven predictive models, integrating diverse clinical, biological, and imaging data, have emerged to forecast adverse events in procedures such as aortic aneurysm repair and carotid disease interventions. These advancements enable the identification of patients who stand to benefit most from surgical interventions, thus advancing precision medicine in vascular surgery.[33]

Surgeons leverage AI to evaluate patient risks, predict surgical outcomes, and determine optimal interventions. Moreover, AI-driven simulations in medical training enhance the proficiency of novice surgeons in performing essential endovascular procedures, ultimately enhancing patient care and surgical outcomes.[34]

The application of AI models in clinical practice is challenged by the need for comprehensive clinical validation, efficient resource management, and transparent decision-making processes. Addressing ethical concerns and ensuring equitable deployment of AI across diverse demographics are pivotal considerations, underscoring the critical importance of establishing clear guidelines and robust policy frameworks. [7, 8, 31] Key issues such as data security, informed consent, and algorithmic biases must be navigated carefully to responsibly implement [35] Furthermore, enhancing the quality of future research and its clinical application requires adherence to upgraded and standardized guidelines like prediction model risk of bias assessment tool (PROBAST) » PROBAST-AI and transparent reporting of a multivariable prediction model of individual prognosis or diagnosis (TRIPOD) » TRIPOD-AI, which are critical for transparent and reliable AI model development and evaluation.[36]

Advancements in AI for vascular surgery, particularly in carotid procedures, are set to revolutionize clinical practice. Ongoing research is increasingly integrating AI with advanced imaging techniques and genomic data to enhance risk prediction models for stroke and refine treatment strategies. The development of AI-driven intraoperative guidance systems aims to optimize surgical precision and patient outcomes by providing real-time decision support to surgeons. Furthermore, researchers are exploring the application of deep learning algorithms to uncover novel biomarkers and therapeutic targets in carotid artery disease, facilitating more personalized and effective interventions. These advancements underscore AI's potential to not only improve diagnostic accuracy and procedural outcomes but also to pave the way for tailored therapeutic approaches that consider individual patient profiles and genetic susceptibilities.[37]

Collaboration between AI experts and clinicians is pivotal for developing patient-centered AI tools. This synergy

Table 1 **Characteristics of the articles in the literature review that applied machine learning in carotid plaque detection**

Study	Year	Study design	Total Patients (n)	Application	Clinical outcome	Main Predictors
Guang et al.	2021	Prospective multicenter	205	Predicting carotid plaque vulnerability	DL-DCCP in CEUS video demonstrated superior diagnostic accuracy to assess the neovascularization of carotid plaques compared with two experienced radiologists who manually classified plaque vulnerability	NR
Huang et al.	2022	Prospective	548	Identifying symptomatic carotid plaques	A nomogram incorporating clinical and conventional US and US-based radiomics had high sensitivity, specificity, and accuracy for identification of symptomatic carotid plaques	Hypertension, hsCRP, smoking, plaque sphericity plaque echogenicity, remodeling index
Jamthikar et al.	2019	Retrospective	202	CV/stroke risk stratification	Developed a ML-based risk stratification system of patients for preventing the occurrence of CV/stroke events	HbA1c, PS and cIMTave
Yeh et al.	2022	Retrospective	538	Predicting carotid stenosis severity	Random forest model, identified several potential predictors to accurately classify artery stenosis	Peak systolic velocity – key predictor in unilateral ICA
Le et al.	2021	Retrospective	41	Predicting stroke	ElasticNet model achieved the highest performance identifying culprit and non-culprit arteries and could improve stroke prediction	GLDM: Dependence Variance GLSZM: Grey Level NonU- niformity GLRLM: Long Run High Grey Level Emphasis
Xia et al.	2023	Retrospective	179	Predicting TIA in patients with mild carotid stenosis	RF model based on radiomics features and clinical features showed the best performance predicting the occurrence of cerebrovascular events	3D diameter LDL UA

CEUS - carotid plaque contrast-enhanced ultrasound; cIMTave - carotid intima-media thickness average; CV – cardiovascular; DL-DCCP - deep learning-based detection and classification of carotid plaque; GLDM - Grey Level Dependence Matrix; GLSZM - Grey Level Size Zone Matrix; GLRLM - Grey Level Run Length Matrix Features; HbA1c - glycated hemoglobin; hsCRP - high-sensitivity C-reactive protein; ICA – internal carotid artery; LDL - low-density lipoprotein; ML – machine learning; NR – not reported; PS - plaque score; RF – random forest; TIA- transient ischemic attack; UA - uric acid; US – ultrasonography.

is essential for effectively integrating AI into clinical practice, especially in complex conditions like vascular surgery. Future endeavors should focus on refining AI systems to ensure reliability across diverse patient populations and healthcare settings.

Despite these hurdles, ML holds significant potential to improve clinical decision-making in vascular surgery, signifying a pivotal phase of advancement in the field.

CONCLUSION

The integration of AI and ML into vascular surgery, especially to address CS, represents a transformative step forward. These technologies have greatly enhanced the accuracy of medical imaging, which is crucial for evaluating CS and guiding surgical interventions and best medical treatment. AI's role in improving risk assessment and predicting patient outcomes for CS offers an edge over traditional methods.

However, integrating AI into regular clinical practice requires addressing clinical validation and data privacy challenges. Despite these challenges, AI and ML hold immense potential to improve decision-making in vascular surgery, pushing the field toward more personalized and safer patient care. The future success of AI in this domain hinges on continued collaboration between AI professionals and medical practitioners.

Table 2 **Summary of the articles that applied AI to carotid stenosis screening**

Study	Year	Study design	Total Patients (n)	Application	Clinical outcome	Main Predictors
Yu et al.	2021	Case-control	2732	Screening ACS	MLP and XGBoost models showed the best performance to screen ACS in patients without risk factors	Age, BP, HCY and HDL-c
Yin et al.	2020	Cross sectional	2841	Predicting ACS	RF can be used to detect ACS among high risk patients of stroke	Family history of dyslipidemia, elevated LDL-c, reduced HDL-c, aging, and low BMI
Fan et al.	2021	Retrospective	18441	Predicting ACS	LR achieved the best performance and in the testing set, predicted 1045/1966 ACS and 3088/3566 non-ACS	Age, systolic BP, glucose, HDL-c and platelet count
Poorthuis et al.	2020	Systematic review	596 469	Predicting high risk of ACS	ACS can be selected using a prediction model and allows the initiation or intensification of cardiovascular medical therapy	Age, sex, smoking, hypertension, hypercholesterolemia, diabetes mellitus, MI, stroke, or TIA, height, measured blood pressure and blood lipids
Kigka et al.	2022	Prospective	881	Diagnosis and identification of ACS	RF showed the highest performance in detecting asymptomatic CAS, which could be beneficial in stratifying the risk of CAD and initiating early management of asymptomatic patients	Aneurysm disease, BMI, weight, height and HLP

ACS - asymptomatic carotid stenosis; BMI - body mass index; BP - blood pressure; CAD - carotid artery disease; CAS – carotid atherosclerosis; HCY –homocysteine; HDL-c - high-density lipoprotein cholesterol; HLP – hyperlipoproteinemia; LDL-c – low-density lipoprotein cholesterol; LR – logistic Regression; MI – myocardial infarction; MLP - multilayer perceptron; RF – random Forest; TIA- transient ischemic attack; XGBoost – Extreme Gradient Boosting.

ABBREVIATION LIST

AI Artificial intelligence
ACS Asymptomatic carotid stenosis
ASA American Society of Anesthesiologists
AUC Area under the curve
BP Blood pressure
BMI Body mass index
CAS Carotid stenting
CEA Carotid endarterectomy
CEMRA Contrast-enhanced magnetic resonance angiography
cIMTave Carotid intima-media thickness average
cIMT Carotid intima-media thickness
CHF Congestive heart failure
CTA Computed tomography angiography
CV Cardiovascular
CS Carotid stenosis
DL Deep learning
DSA Digital subtraction angiography
ECST European Carotid Surgery Trial
EPOH Early phase postoperative hypertension
FBS Fasting blood sugar
FH Family history
GBRT Gradient boosted regression trees
HbA1c Glycated hemoglobin
HDL-c High-density lipoprotein cholesterol
HT Hypertension
ICA Internal carotid
LDL-c Low-density lipoprotein cholesterol
LR Logistic regression
ML Machine learning
MI Myocardial infarction
MICA The Gupta Perioperative Myocardial Infarct or Cardiac Arrest
NASCET North American Symptomatic Carotid Endarterectomy Trial
PROBAST Prediction model risk of bias assessment tool
PS Plaque score
RF Random forest
TC Total cholesterol
TIA Transient ischemic attack
TG Triglyceride
TRIPOD Transparent reporting of a multivariable prediction model of individual prognosis or diagnosis
US Ultrasound
XGBoost Extreme gradient boosting (algorithm)

Table 3 **Summary of articles of AI research focusing on risk stratification**

Study	Year	Study design	Total Patients (n)	Application	Clinical outcome	Main Predictors
Pereira-Macedo et al.	2022	Prospective	194	Predicting IND during CACC in CEA	MICA risk score might play a role in stratifying patients for IND during CEA	BMI > 30 kg/m2, obesity, higher MICA risk score, and higher contralateral stenosis
Bai et al.	2020	Retrospective	443	Screening key predictor factors of early cerebral infarction and myocardial infarction after CEA	ML model identified eight predicting factors, however further sudies are needed	Mean arterial pressure during occlusion, mean arterial pressure after the operation, the standard deviation of systolic pressure during occlusion, diastolic pressure during occlusion, mean arterial pressure entering the room, systolic pressure during occlusion, BMI and age
Matsuo et al.	2022	Retrospective	170	Predicting 30-day ischemic stroke after CEA or CAS	XGBoost model had the highest predictive performance and enables preoperative calculation of post-CEA/CAS stroke risk	ICA-PSV, LDL-c, and the type of procedure (CEA or CAS)
Tan et al.	2020	Retrospective	367	Predicting EPOH after CEA	GBRT helps to identify high risk patients for EPOH and reduce complications	Peak systolic BP, DcT, propofol, ipsilateral severity of stenosis, cardiac index, fentanyl, and ephedrine
Li et al.	2023	Prospective	38853	Predicting 30-day major adverse cardiovascular events (stroke, MI or death) after CEA	XGBoost model achieved the best performance for predicting 30-day MACE following CEA and have potential to be used in the perioperative management of patients, aiming to reduce adverse outcomes	Symptomatic CS, history of congestive heart failure, ASA class, functional status, transfer from another hospital, preoperative dialysis, physiologic high-risk factor, revision CEA, anatomic high-risk factor, and urgency of surgery

ASA- American Society of Anesthesiologists; BMI - mody mass index; BP – blood pressure; CACC- carotid cross-clamping; CAS - carotid stenting; CS – carotid artery stenosis; CEA - carotid endarterectomy; DcT - deceleration time of the E-wave velocity; EPOH - early-phase post-operative hypertension; GBRT - gradient boosted regression trees; ICA -PSV - internal carotid artery peak systolic velocity; IND - intraoperative neurologic deficits; LDL-c – low-density lipoprotein cholesterol; MACE- major adverse cardiovascular events; MI – myocardial infarction; MICA - The Gupta Perioperative Myocardial Infarct or Cardiac Arrest; ML - machine learning; XGBoost – Extreme Gradient Boosting.

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