Table S1. Artificial intelligence in ultrasound in symptomatic carotid plaque.

References	AI-based Approach	Data Collection	Study Aims and Clinical Implications	Main Results	Limitations
Zouh et al. (2019)	CNNS (*U-shaped structured CNNs: U-Net*)	26 3D-carotid US images (34 plaques)	Automatic segmentation of the carotid arterial wall for the early diagnosis of atherosclerotic disease	High accuracy in detecting atherosclerotic plaques (DSC 0.907) compared with manual segmentation	Limitated labeled examples for a fully-automatic segmentation; small size of cohort study
Meshram et al. (2020)	CNNs (*Dilated U-Net*)	352 US images from 101 patients with severe stenotic carotid disease	Automatic and semi-automatic segmentation for the detection of critical carotid stenosis (>70%) needing reperfusion strategy (endarterectomy)	Dilated U-Net has a high accuracy (DSC 0.88) in the diagnosis of critical atherosclerotic disease	2D-carotid US images-based on algorithm; bounding box by a sonographer input is required for segmentation; reduction of accuracy in the presence of acoustic shadowing
Loizou et al. (2007)	CNNs (*Snake segmentation method*)	100 longitudinal US images of the carotid artery	Automatic segmentation using the snake segmentation algorithm to measure IMT for estimating CV risk	No differences were found between the snakes segmentation and the manual segmentation measurements	Less accuracy in case of irregularity of the arterial wall; need of pre-processing of the US images
Menchón-Lara et al. (2015)	ML	55 longitudinal US images of CCA	Automatic segmentation using a Machine Learning and Statistical Pattern Recognition to measure IMT from ultrasound CCA images to assess the risk of cerebrovascular events	No differences were found between the snakes segmentation and the manual segmentation measurements	Less accuracy in case of irregularity of the arterial wall
Biswas et al. (2018)	DL	396 2D-US images of CCA from 203 patients	Automatic measurement of carotid IMT as a biomarker of CV risk and for stroke monitoring	DL-based approaches are superior to the nonintelligence based on-methods, providing up to the 20% improvement in cIMT measure compared with sonographers' readings	Datasets limited to diabetic Japanese patients and requirement of further analysis in a multiethnic patient population; extension to a web-based version to increase the reproducibility of the analysis
Jain et al. (2021)	DL (*U-Net architecture*)	330 2D-US images of CCA from 165 patients	Early detection of atherosclerotic carotid disease using a U-Net based on-DL method able to provide the segmentation of the atherosclerotic wall with low plaque	The system showed a high accuracy, dice-similarity and correlation-coefficient (>90%, >75% and >0.80 respectively) in detecting and classifying 268 carotid plaques.	The high-intensity zone of the media region of the plaques did not allow for performing the best partial volume in the region of interest
Zhang et al. (2022)	CNNs (*SegNet*)	US and HRMRI images from 150 patients with acute ischemic stroke or TIA	Evaluation of the characteristics of the atherosclerotic plaques basing on US and HRMRI texture analysis with the aim to identify vulnerable plaques and predict the risk of disability and recurrence of ischemic events	The combined model showed a high accuracy, sensitivity and specificity (79.05, 85.94 and 68.29%) in differentiating vulnerable and stable plaques	Bidirectional cohort study increases selection bias; manual delineation of ROI; relative small number of cases; pathological confirmation not available for all the cases
Skandha et al. (2020)	DL (*optimized DCNN11A5 system*)	2000 US carotid scans from 346 patients (196 patients with symptomatic plaque and 150 with asymptomatic plaque)	Correlation between the echogenic characteristics and the vulnerability of the atherosclerotic lesions in order to provide an automated model to classify carotid plaques helping to guide the surgeons' decision to better therapeutic strategy	The DCNN model demonstrated a better performance compared with other ML models, with an accuracy of 95.66% (AUC 0.956) in identifying vulnerable plaques	Moderate size of the cohort study; limited availability of the supercomputer (using NVIDIA DGX v-100) during the study
Sousa et al. (2016)	DL	Longitudinal and transversal set of B-mode	Identification of vulnerable plaques basing on the haemodynamic	The simulation model was able to identify haemodynamic alterations	Small size of the population study; wall compliance affected by profile irregularity.

		images from two patients (patient 1 with CCA bifurcation stenosis and patient 2 without visible carotid plaques)	characteristics of CCA plaques (velocity and WSS) to create a US-computational simulation model to improve diagnostic and treatment management of carotid atherosclerosis	related with CCA bifurcation stenosis, helping to select patients at higher risk of ischemic stroke	
Azzopardi et al. (2020)	DCNNs	81000 US images from a population of 15 people with different grades of carotid stenosis (between 0% and 60%)	Application of DCNN models in plaque burden estimating MAB and LIB for early prediction the risk of atherosclerotic disease	The model showed high accuracy for automated segmentation of MAB and LIB (96.2% and 92.5% respectively) using trasverse US images	Limited size of the dataset; limited imaging platform employed; dependence on expert labelling for manual segmentation used for training.
Saba et al. (2021)	Fully CNNs (*AtheroEdge™softwar*)	IMT and plaque images from US studies	Estimation of the plaque area tracing the distance between the lumen-intima and media-adventitia borders to evaluate critical CCA stenosis	The model was associated with a high accuracy in providing the automatic detection of plaque area relating with flow turbolence and vulnerability	Failure around noisy corner; need of clear delineation.
Johri et al. (2021)	ML (AtheroEdge-MCDL$_{AI}$:AE3.0$_{DL}$ and AtheroPoint™)	IMT and plaque characteristics (area, height and neovascularisation) of 459 patients	Evaluation of CVD risk combining ultrasound imaging and conventional cardiovascular risk calculators	The study demonstrated a higher performance of the ML algorithm in predicting cardio- and cerebrovascular events than the conventional approaches based on clinical features	Small size of the cohort, higher baseline cardiovascular risk of the population study, lack in the evaluation of lipidic profile.
Akkus et al. (2015)	ML (CINQS)	45 CEUS-images from 29 symptomatic patients	Diagnosis of intraplaque neovasculatisation as marker of plaque vulnerability	The model was able to identify two best parameters (time integrated IPN surface area and statistical segmentation-based IPN surface area) for the diagnosis of IPN, showing a high accuracy (AUC >0.9) in the identification of vulnerable plaques	Use of consensus visual IPN scoring, small size of the cohort, lack of histopathological confirmation
Goremati et al. (2020)	ML-RF	B-mode US images obtained from 77 patients (18 symptomatic and 59 asymptomatic patients)	Correlation between the plaque motion and the vulnerability of the plaque, considering the characteristics of echogenicity, degree of stenosis and symptomaticity	The study showed that plaque asynchronism was related with symptomaticity, echogenicity and high-grade stenosis of plaque, proposing an accurate automated method (AUC of 0.81, 0.79, 0.89 and 0.90, for the association of plaque motion with echogenicity, symptomaticity, stenosis degree and plaque risk respectively) to detect vulnerable plaques for assessing stroke risk.	Moderate size of the cohort, heterogenity of the dataset

AUC: area under the cruves; CCA: common carotid artery; CNN: convolutional neural networks; CV: cardiovascular; DCNN: deep convolutional neural networks; DL: deep learning; DSC: Dice similarity coefficient; HRMRI: high-resolution magnetic resonance imaging; IMT: intima-media thickening; LIB: lumen - Intima boundary; MAB: media-adventitia boundary; ML: machine learning; ROI: region of interest; TIA: transient ischemic attack; US: ultrasound; WSS: wall shear stress.

Table S2. Main Studies using AI applied to vascular CT.

References	Study Aim	Date of Publication	Ai-Based Approaches	Main Results	Clinical Implications	Limitations
Buckler et al.	Evaluation of the accuracy of a machine-learning software for determining plaque risk phenotype as compared to expert pathologists (histologic ground truth).	2022	DL, CNN	Great agreement in validation with histological ground truth plaque risk phenotypes. Identification of plaque type (stable plaque, and minimal disease). lumen percent diameter stenosis on CTA shows poor correlation with a histologically defined high-risk plaque	Refining patient risk and potentially better-informing treatment strategies.	Clinical outcomes of the procedure or subsequent clinical events were not assessed. The classification into three risk groups may oversimplify the individual and plaque-specific risk.
Le et al.	Evaluate the robustness and reproducibility of carotid CT angiography radiomics implemented with ML and its impact on the ability to identify culprit carotid arteries in stroke and TIA patients	2021	ML	Was identified a set of radiomic features that are robust, non-redundant and have superior predictive performance, for the classification of culprit versus non-culprit carotid arteries in patients with stroke and TIA.	Could improve stroke prediction and target therapies to those at highest risk.	Retrospective nature. All images were acquired using the same scanner in one centre. Imaging dataset captured information from culprit carotid arteries after plaque rupture. Only unfiltered radiomic features Were investigated.
Kigka VI et al.	To develop a machine learning model for the identification of high risk plaques using non imaging based features (clinical data, biomarkers, serum markers) and non-invasive imaging based features.	2021	ML	the highest accuracy observed and area under the curve was 0.76 and 0.73, respectively	Patient management and selection of medical therapy. Noninvasive.	Not indicated
Kigka et al.	to present a machine learning model for the diagnosis and identification of individuals of asymptomatic carotid artery stenosis, using as input typical health data (demographics, clinical data, risk factors and medical treatment)	2022	ML	classification of individuals into high risk and low risk individuals. Accuracy 0.82 and an area under curve 0.9	Patient management and selection of medical therapy. Noninvasive	Not indicated
Rava et al.	To assess the ability of Canon's AUTOStroke Solution LVO application in properly detecting and locating LVOs in acute ischemic stroke patients.	2021	ML	Accurately identification of ICA and M1 MCA occlusions. Nearly perfectly ruling out when an LVO was not present.	Rapid identification of patients who need to perform mechanical thrombectomy in order to regain more neurological function	M2 MCA occlusion detection needs further improvement based on the sensitivity results displayed by the LVO detection algorithm.

Rodrigues, Barreira et al.	To evaluate the performance of an AI-based algorithm for LVO detection in acute ischemic stroke.	2022	ML	Accurately identification of ICA and M1 MCA occlusions.	Rapid identification of patients who need to perform mechanical thrombectomy in order to regain more neurological function	Not indicated
Tatsugami et al.	Comparison of image quality of coronary CTA subjected to DL–based image restoration method with images subjected to hybrid iterative reconstruction .	2019	DL, CNN	Reduction of image noise and improves of image quality.	image quality improvement. Reduction in radiation exposure.	Small study population. Diagnostic accuracy of coronary CTA images not confirmed in comparison with invasive coronary angiography.
Benz et al.	Validation of reconstruction for coronary computed tomography angiography	2020	DL	Deep-learning image reconstruction in CCTA compared to ASiR-V has shown superior image quality at equal diagnostic accuracy.	image quality improvement and non-inferior diagnostic accuracy compared to ICA	inclusion of patients with a high burden of CAD. DL reconstruction algorithm are vendor-specific.
Chandrashekar et al.	Automated segmentation of pathological blood vessels in CT images acquired with contrast agent and NCCT.	2020	DL, CNN	DL-U-Net in extracting lumen and the wall structure of the aortic aneurysm from CT angiograms was compared against a generic 3-D U-Net and displayed superior results	Standardize aneurysmal disease management analyzing complex geometries and morphologies. Avoid contrast agents.	Not indicated
Olive-Gadea et al.	Validation of machine learning algorithm (MethinksLVO) to identify LVO on NCCT	2020	DL	Identification of LVO with MethinksLVO and MethinksLVO+ has shown high sensitivity, specificity and high predictive values.	To reduce the need to perform CTA, generate alarms, and increase the efficiency of patient transfers in stroke networks. Two minute performance.	MethinksLVO was tested against CTA instead of gold standard digital subtraction angiography. population may not accurately represent patients with suspected stroke admitted in small community hospitals.

ML, machine learning; DL, deep learning; CNN, convolutional neural network; CTA, computed tomography angiography; CCTA, contrast computed tomography angiography; TIA, transient ischemic attack; ICA, internal carotid artery; MCA, middle cerebral artery; ASiR-V, adaptive statistical iterative reconstruction; ICA, invasive coronary angiography; CAD, coronary artery disease; LVO, large vessel occlusion; NCCT, non-contrast computed tomography.

Table S3. MRI-applicated ai for the characterization of atherosclerotic plaques.

References	AI-Based Approaches	Data Collection	Study Aims and Clinical Implications	Results
Adame I. M et al. *(2004)*	ML (model-based segmentation and fuzzy clustering)	17 subjects (10 asymptomatic and 7 symptomatic): 50 images (23 PDW and 27 T1W) 46 presented a stenosis (10 in the CCA and 36 in the ICA) and 4 correspond to non-stenotic vessels	To develop an automated contour detection technique for tracing the lumen, outer boundary and plaque contours in carotid MR short-axis black-blood images	Excellent correspondence between automatic and manual area measurements for lumen (r=0.92) and outer (r= 0.91), acceptable correspondence for fibrous cap thickness (r= 0.71)
Wu J. *et al.* *(2019)*	CNNs (deep U-shape)	Image stream from the BB-VWMRI image and morphology stream from the obtained vessel wall map are extracted from two deep CNNs	Developing a deep morphology aided diagnosis (DeepMAD) network for automated segmentation of the VW of carotid artery and for automated diagnosis of the carotid atherosclerosis with the black-blood (BB) VW-MRI	**Segmentation performances** 0.9594 (lumen) 0.9657 (outer wall) **Accuracy** 0.8916 **AUC** 0.9503
Tsakanikas V.D et al. *(2020)*	CNNs	~200 RM images obtained from 30 patients enrolled in two clinical centres in the TAXINOMISIS study	Presenting a new carotid vessel segmentation algorithm to produce a 3D meshed model of the carotid bifurcation and smaller branches, using multispectral MR image series	**Accuracy** 99.1% (lumen area) 92.6% (perimeter)
Shi Z. et al. *(2020)*	ML (step-wise regression analysis)	247 patients with intracranial atherosclerosis	To evaluate differences in histogram features between culprit and nonculprit intracranial atherosclerosis using high-resolution magnetic resonance imaging	**AUC** 0.831 **Sensitivity** 76 % **Specificity** 77 %
Zhang R. et al. *(2020)*	ML (LASSO algorithm)	162 patients with carotid stenosis (n = 121 training cohort; n = 41 test cohort)	To build a high-risk plaque MRI-based model (HRPMM) using radiomics features and ML for differentiating symptomatic from asymptomatic carotid plaques	**AUC** 0.989 (training cohort) 0.986 (test cohort)
Yang F et al. *(2003)*	ML (dynamic programming)	62 T1W MR images from six human ilio-femoral specimens	Developing and testing a computerized method for segmentation of arterial wall layers and plaque from high-resolution volumetric MR images	Border positioning errors: 0.1 ± 0.1 (lumen) 0.0 ± 0.1 (internal elastic lamina) 0.1 ± 0.1 mm (external elastic lamina)

AI: artificial intelligence; AUC: area under the curves; CNNs: convolutional neural networks; DL: deep-learning; DUS: Doppler ultrasound; ICA: internal carotid artery; LAAS: large artery atherosclerosis; LVO: large vessel occlusion; ML: machine-learning; VW: vessel wall; BB-VWMRI: black blood vessel wall magnetic resonance imaging; HR-MRI: high-resolution magnetic resonance imaging; HRPMM: high-risk plaque MRI-based model; LASSO: least absolute shrinkage and selection operator; PDW: proton density weighted; T1W:T1 weighted; MR: magnetic resonance.