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| **title** | **author** | **country** | **No. Of patients (train vs test)** | **Participant type** | **purpose** | **conclusions** |
| Machine learning-directed electrical impedance tomography to predict metabolically vulnerable plaques | Chen et al. 2024  (Bioengineering Transla Med) | USA | 270 (216, 54) | atherosclerotic plaques | predict the metabolic vulnerability of atherosclerotic lesions. |  |
| Detection of Asymptomatic Carotid Artery Stenosis through Machine Learning | Vassiliki  Et al 2022 | UK | 881 cases (443 - low and 438- high risk) | patients admitted to the Clinic for Vascular and endovascular surgery, in the University Clinical Center of Serbia at the period from 01.03.2021-01.01.2022. | classify the asymptomatic individuals into high and low risk. | A simple machine learning model that considers typical health data for the detection of asymptomatic patients  with a carotid stenosis higher than 50%. |
| Detection of Asymptomatic Carotid Artery Stenosis in High-Risk Inviduals of Stroke using a Machine-Learning Algorithm | Yin and Yu 2020 | China | 2481 | individuals with high risk for strokes involved in the China national Stroke screening and prevention project (CNSSPP) | Investigate a machine learning algorithm for the detection of ACS among high-risk population based on the associated risk factors. | Aging, dyslipidemia, low level of high-density lipoprotein cholesterol (HDL-c), high level of low-density lipoprotein cholesterol (LDL-c) and low body mass index (BMI) are the most significant risk factors of ACS. |
| Machine learning models for screening carotid atherosclerosis in asymptomatic adults | Jian Yu et al 2021 | China | 2732 | A total of 2732 asymptomatic subjects for routine physical examination in our hospital were included in the study. | develop machine learning models to screen CAS in asymptomatic adults. | The models may provide an effective and applicable method for physician and primary care doctors to screen asymptomatic CAS without risk factors in general population and improve risk predictions and preventions of cardiovascular and cerebrovascular events in asymptomatic adults. |
| The prediction of asymptomatic carotid atherosclerosis with electronic health records: a comparative study of six machine learning models | Fan, Chen et al 2021. | China | 18441 (medium age=50) | subjects examined in the Department of Health Management at The Second Affiliated Hospital of Xi’an Jiaotong University from April 19, 2010, to November 15, 2019. | Predict asymptomatic CAS subjects using electronic health records. | logistic regression model produced a more accurate and effective prediction for asymptomatic CAS among six machines.  learning models for prediction |
| Machine learning detects symptomatic  patients with carotid plaques based on 6-type  calcium confguration classifcation on CT  angiography | Francesco Pisu et al 2023 | italy | 790(median age 72) and 159(median age 68) | diagnostic study performed in three tertiary centers (Azienda OspedalieroUniversitaria di Cagliari [site A], Stanford University  Hospital [site B] and St, Franziskus Hospital Münster  [site C]). | develop and validate a CT angiography  (CTA)–based machine learning (ML) model that uses carotid plaques 6-type calcium grading, and clinical parameters  to identify CVE patients with bilateral plaques. | The developed model can identify symptomatic patients using plaques calcium confguration data  and clinical information with reasonable diagnostic accuracy. |
| Symptomatic vs. Asymptomatic Plaque Classification in Carotid Ultrasound | Acharya, Faust et al 2011 | UK | 348 carotid plaques images (150 asym and 196 symptomatic) | The images were collected from February 1999 to September 2000 and they come from patients which were referred to the vascular laboratory for diagnostic carotid ultrasound to detect the presence and severity of internal carotid stenosis. | The study wants to build a computer-aided diagnosis (CAD) system which analyzes ultrasound images and classifies them into symptomatic and asymptomatic based on the textural features and uses automatized classifiers. | The CAD system built using SVM with radial basis kernel gives a good diagnosis accuracy. Symptomatic asymptomatic carotid index has also been proposed to identify the symptomatic and asymptomatic carotid ultrasound images using a single number. |
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| Object-Specific Four-Path Network for Stroke Risk  Stratification of Carotid Arteries in Ultrasound Images | Wei Ma et al 2022 | China | 333 patients with a total of 1332 images | patients with atherosclerotic events and 216  event-free patients, were analyzed | propose an object-specific  four-path network (OSFP-Net) for stroke risk assessment by integrating ultrasound carotid plaques in both transverse and  longitudinal sections of the bilateral carotid arteries | The experimental results demonstrated that our network  is more effective and outperforms such popular networks as  ResNext50, DenseNet121, and EfficientNet-b7 in terms of  accuracy, sensitivity, specificity, precision, and F1-score. |
| Radiomics and artificial neural  networks modelling for  identification of high-risk carotid  plaques | Chengzhi Gui et al 2023 | China | 104 patients with carotid artery stenosis | patients with carotid artery stenosis, who were diagnosed with either  symptomatic plaques (SPs) or asymptomatic plaques (ASPs), in two medical  centers | investigate the classification of symptomatic  plaques by evaluating the models generated via two different approaches, a  radiomics-based machine learning (ML) approach, and an end-to-end learning  approach which utilized deep learning (DL) techniques with several  representative model frameworks. | The DL models were able to accurately differentiate between  symptomatic and asymptomatic carotid plaques with limited data, which  outperformed radiomics-based ML models in identifying symptomatic plaques. |
| Stratification of carotid atheromatous plaque using interpretable deep learning methods on B-mode ultrasound images | Ganitidis, Athanasiou  Et al. 2021 | Greece | 74 (58 asymptomatic and 16 symptiomatic) | patients with carotid atheromatous plaque coming from the Attijon General University Hospital of Athens that gave their consent for the study | leveraging the feature extraction capabilities of deep Convolutional Neural Networks along with interpretability methods towards the development of an interpretable model for the risk stratification of patients with carotid atheromatous plaque | Both the feature extraction and the classification was being successfully done by a CNN. Given the problem that it is a blackbox, interpretable methods did allow to better understand which parts of the images of the plaques mostly influence the classification. Further work needs to be done to investigate the highly imbalanced dataset. |
| SSCPC-Net: Classification of carotid plaques in ultrasound images using a self-supervised convolutional neural network | Yan, Gan et al 2022 | China | 844 patients and 1,270 longitudinal plaque images obtained | Patients that participated a study by Zhongnan Hospital of Wuhan University | Build a self-supervised carotid plaque classification network that could distinguish between three types of plaques and find a solution for the problem that the number of carotid plaque labeling images in clinical practice is small. | SSCPC-Net could effectively improve the classification accuracy of basic ResNet. It could also effectively alleviate the problem of insufficient labeling of training images. |
| A self-supervised fusion network for carotid plaque ultrasound image classification | Zhang, Gan et al. 2024 | China | 1270 carotid plaque images from 844 individuals | patients at Zhongnan Hospital (Wuhan, China) | Provide a better method than SLL for dealing with the problem of limited labeled images. | Fusion-SSL could be beneficial for the classification of carotid plaques and the early warning of a stroke in clinical practice |
| Ultrasound‐based internal carotid artery plaque characterization using deep learning paradigm on a supercomputer: a cardiovascular disease/stroke risk assessment system | Saba, Sanagala et al 2021 | USA | 346 carotid ultrasound-based delineated plaques (196 symptomatic and 150 asymptomatic, mean age 69.9 ± 7.8 years, with 39% females) | Data used for previous work  All patients with internal carotid artery (ICA) stenosis of 50% to 99% | develop and design an automated carotid plaque characterization and classification system into binary classes, namely symptomatic and asymptomatic types via the deep learning (DL) framework implemented on a supercomputer. | This is the first study of its kind to characterize and classify carotid plaques into symptomatic and asymptomatic categories using a deep learning paradigm implemented on a supercomputer. The deep learning system shows an improvement of 6.0% compared with previous methods. |

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| **study** | **modality** | **segmentation** | **feature** | **Modeling method** | **No imaging features** **included in the model.** | **AUC in training set** | **Classification measures** | **Validation and method** | **Data preprocessing** | **Feature selection** |
| Machine learning-directed electrical impedance tomography to predict metabolically vulnerable plaques | EIS data | Not needed | oxLDL (oxidized low-density lipoprotein) | LR, ResNet-7, DenseNet-9 | NA | 1 for the best model (DenseNet-9) | Confusion matrix | NA |  |  |
| Detection of Asymptomatic Carotid Artery Stenosis through Machine Learning | CDU | Not needed |  | e J48 algorithm, Random Forests (RF), Naive Bayes (NB), Support Vector Machine (SVM) and Artificial Neural Networks (ANN). | 21 (continuous and non) | 0.9 for the best model (RF with relief technique) | AUC, Acc, sensitivity and the specificity | 10 FCV | Data curation | the relief technique (case 1), the principal components analysis (case 2), the OneR (case 3), the Infogain Ratio (case 4), the Gain Ratio (case 5), the Correlation Attribute Evaluation (Case 6), the Class Attribute Evaluation (case 7) and the Correlation based Feature Selection (case 8). |
| Detection of Asymptomatic Carotid Artery Stenosis in High-Risk Inviduals of Stroke using a Machine-Learning Algorithm | Carotid duplex scans | Not needed |  | Random forest using TensorFlow, using CART Tree as weak classifier and the Gini index to build the tree. | 30 | 0.927 for training and 0.888 for testing | AUC and ROC | 80-20 Random split of the dataset | Removal of similar, duplicated and non-relevant variables, normalization. | Only 30 out of 53 risk factors collected through interview were kept (NA how) |
| Machine learning models for screening carotid atherosclerosis in asymptomatic adults | Carotid duplex ultrasonography | Not specified |  | MLP, XGBoost, SVM, Random Forest,  Decision Tree | 17 | MLP highest accuracy (0.748) with AUC (0.766) | AUC, ROC and confusion matrix metrics | 80-20 split and 10-Fold cross validation. | Initial selection of patients based on their medical history. | The candidate's features were collected from the electronic medical record. |
| The prediction of asymptomatic carotid atherosclerosis with electronic health records: a comparative study of six machine learning models | carotid B-mode ultrasonography  and routine clinical data of medical check-up | Not needed |  | logistic regression [LR], random forest [RF], decision tree [DT], eXtreme Gradient Boosting [XGB], Gaussian Naive Bayes [GNB], and K-Nearest Neighbour [KNN] | 19 | AUCROC= 0.809, ACC= 74.7%, F1=59.9%,  Sensitivity=53.2%  Specificity=86.8% for the best model found that is LR | area under the receiver operating characteristic curve (AUCROC), accuracy (ACC), and F1 score (F1). | 70-30 split and 10 FCV | Categorical features encoded as binary input feature and continuous features scaled in the range [0,1] | Binary logistic regression to select significant features. Out of 59 features, 19 were used as input for the models. |
| Machine learning detects symptomatic  patients with carotid plaques based on 6-type  calcium confguration classifcation on CT  angiography | CTA examinations | Not specified | The six subgroups were type 1, complete absence of calcification within the plaque; type 2, intimal or superficial calcifications; type 3, deep or bulky calcifications; type 4, adventitial calcifications with internal soft plaque  of<2 mm; negative rim sign; type 5, mixed patterns with  intimal and bulky calcifications; and type 6, positive rim  sign. | tree-based gradient boosting generalized additive modeling (GB-GAM) used to obtain 5 different models | 36 | AUROC of 0.71 | ROC and precision-recall curve | 10 repetitions of the tenfold stratified CV.  90-10 split | Carotid plaques were classifed into six subgroups based on the presence and location of calcifcations, | Variables are ranked by average absolute impact on predictions made by the model  trained using all variables on all available derivation data |
| Symptomatic vs. Asymptomatic Plaque Classification in Carotid Ultrasound | Ultrasound images | Not specified | Textural (surface and structure of the image) | **AdaBoost** with 5 distinct configurations: Least Squares, Maximum- Likelihood, Normal Density Discriminant Function, Pocket, and Stumps. and **Support Vector Machine**, with 5 different kernel configurations: linear kernel, polynomial kernel configurations of different orders and radial basis function kernels. | 4 (standard deviation, entropy, symmetry and run percentage) | SVM with radial basis function kernel had the best classification result: classification accuracy of 82.4%, sensitivity of 82.9%, and specificity of 82.1% and AUC of 0.818 | TN, FN, TP, FP, accuracy, PPV, Sensitivity, Specificity, AUC | 242 for training and 104 for testing.  Three fold stratified cross validation |  | Features computed using elaboration of the image and the co-occurrence matrix. Then to each of them the p-value is associated and it showed they are all clinically significant |
| Object-Specific Four-Path Network for Stroke Risk  Stratification of Carotid Arteries in Ultrasound Images | Ultrasound carotid plaque | manual segmentation results  were used as the ROIs. |  | Object-Specific Four-Path Network (OSFP-Net) | 4 imaging parameters | 0.976 accuracy, the highest between the popular solutions. AUC of 0.99 | Confusion matrix and AUC ROC | CV with K5 protocol, 80/20 | Data Augmentation and manual segmentation | Deep learning  methods overcome the difficulty in manual definition and  selection of features |
| Radiomics and artificial neural  networks modelling for  identification of high-risk carotid  plaques | HRMRI | ROIs were obtained by manually segmenting  SPACE images using 3D-Slicer | Feature extraction obtained with DenseNet or from radiomic based image anlysis | KNN, LR, SVM, DT, RF, XGBoost, AdaBoost, LightGBM, CatBoost, MLP.  DenseNet  SE-DenseNet  SENet | artificial neural networks that learn effective features from image  data without delineating carotid plaque boundaries | 0.8 AUC with MLP  0.93 AUC with DenseNet | Confusion matrix, AUC, ROC | Repeated K5 cross validation with different parametrization methods | Manual segmentation and volumentations techniques | DL extracts more representative high-level abstract  features from the raw data, while machine learning requires  manual feature selection and design |
| Stratification of carotid atheromatous plaque using interpretable deep learning methods on B-mode ultrasound images | B-mode ultrasound images (videoa) | Done by the radiologist | Feature extraction obtained with the CNN | A six-layer deep CNN used to extract features from the images, followed by a classification stage of two fully connected layers. Use of surrogate models to explain the predictions of the NN, by quantifying the impact of each pixel on the prediction. | unknown | (AUC)= 0.73, sensitivity: 75%, specificity: 70% | Confusion matrix, sensitivity, specifificy, balanced accuracy, AUC | 4 fold cross validation scheme. Random split of the dataset into training, validation and testing sets ( 62%, 13%,25% respectively). To address the highly imbalanced distribution of patients between the symptomatic and asymptomatic an ensemble learning scheme based on a sub-sampling approach was applied along with a two-phase, cost-sensitive strategy of learning. | Manual segmentation | Automatically done by the CNN |
| SSCPC-Net: Classification of carotid plaques in ultrasound images using a self-supervised convolutional neural network | Ultrasound image | NA | Feature extraction obtained with the CNN | A self supervised classification network algorithm: SSCPC-Net which consists of two parts: (1) The self-supervised pretext task training. In this stage, the ordered images are first converted to the shuffled images by the image block shuffling strategy, and then the ordered images and the shuffled images are preprocessed as ResNet’s input to train the network. (2) The self-supervised downstream task training: the preprocessed ordered images are first used as the input of the ResNet, and then the network model obtained in step (1) is transferred to the ResNet in the downstream task to initialize the weight parameters. Finally, after training, the classification result of the carotid plaque is obtained.  Its performance is compared to ShuffleNet-V2, EfficientNet-B0, Resnet101, Rotation Prediction. | unknown | Not defined AUC, 0.856, sensitivity 0.852, specificty 0,924 | Accuracy, sensitivity, specificity | training the pretext task model: random split of training and validation set (8:2). downstream task: random split of training, test and validation set (6:2:2) | 4 steps: (1) The ROI image of each plaque is obtained according to the segmented plaque boundary, and the pixels outside the boundary are set to zero to obtain the preprocessed plaque image; (2) The preprocessed plaque image is padded with zeros to generate a modified square plaque image based on the long side of the original plaque rectangle; (3) The size of the square plaque image obtained in step (2) is normalized to a fixed size of 224×224. | The pretext task, con- structed by an image block shuffling strategy, could obtain the visual features from unlabeled images. These results are passed to the downstream CNN which selects the features automatically |
| A self-supervised fusion network for carotid plaque ultrasound image classification | Ultrasound images | NA | Feature extraction obtained with the CNN | Build a dual-branch residual network (DBResNet) to fuse the two self-supervised network models obtained in step (1). The DBResNet contains three parts: a feature extraction layer, a feature fusion layer, and a fully connected layer. | unknown | AUC: 0.96 with a 100% percentage of labeled image | Accuracy, sensitivity, specificity, precision, G-mean, F1 score, Kappa, PR and ROC curve | randomly divided into a training set and a validation set in a ratio of 0.8:0.2 | Same as above | Feature maps obtained the two self supervised network and then fused together |
| Ultrasound‐based internal carotid artery plaque characterization using deep learning paradigm on a supercomputer: a cardiovascular disease/stroke risk assessment system | Ultrasound images | manual | Feature extraction obtained with the CNN | Atheromatic 2.0: classic convolution neural network consisting of 13 layers | unknown | AUC: 0.91 | AUC, accuracy, ROC curve, | K10 (90% train- ing and 10% testing) cross-validation protocol | Data augmentation performed by using random geometric transformation of the delineated plaque, such as flipping, skewing, and rotating | Automatically done by the CNN |