RESEARCH PAPER

AI-Based Carotid Plaque Detection

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***Abstract*— Many deaths in people around the globe occur due to cardiovascular diseases, especially carotid artery plaque which is mainly responsible for ischemic stroke. If plaque is detected early, many serious complications can be avoided which results in better outcome of patients. In everyday clinical practice, carotid ultrasound imaging is used to examine the carotid artery. However, the interpretation and analysis of these images are usually carried out manually by specialized medical personnel. Executing this task may often take considerable time and depend highly on the operator's experience. This paper proposes an automatic framework to detect these deviations and define their severity using deep learning and machine learning techniques. Through the proposed mechanism, firstly, the plaque is detected from ultrasound images using the ResNet-50 model. After that, this model is fused with a U-Net segmentation model for estimating intima-media thickness. In the end, the features extracted from these 1031 PET/CT images are used as input to the k-Nearest Neighbors machine learning algorithm to enhance performance and provide a specific prediction. The system possesses the accuracy and resolution for classification and segmentation of intravascular ultrasound images that are obtained from the intravascular ultrasound-catherization system. Such processing will certainly be useful in the predictive diagnosis of atherosclerosis and also developing more sophisticated capabilities for plaque assessment. Advancement of computed IVUS may allow further availability of a more large amount of investigator-driven approaches for future clinical decision-making. To implement clinically in real life, we deploy the developed models in a web based on Flask.**

Keywords— Carotid Artery Plaque, Deep Learning, ResNet-50, U-Net, Intima-Media Thickness, KNN, Stroke Prevention.

I. Introduction

Globally, one of the main causes of death is cardiovascular disease, and in this context, stroke is regarded as a serious complication. One of the more annoying factors that cause stroke is a buildup of plaques in carotid arteries, resulting in a blockage of blood flow to the brain. Detection of this plaque at an early stage is very crucial in order to avoid serious consequences. In general clinical practice, a combination of Doppler ultrasonography and manual evaluation of intima-media thickness is commonly used for diagnosis, and this is mostly dependent on the judgment of the practitioner, resulting in inconsistent and/or time-consuming evaluation.

the recent developments in the field of artificial intelligence have introduced new possibilities for improving the analysis of medical images. Deep learning algorithms have the potential to learn meaningful patterns from ultrasound images and assist in efficient detection of plaques. In this paper, the performance of the ResNet50 model is used to analyze carotid ultrasound images and detect whether plaques are present. Additionally, a U-Net model is used to segment the arterial walls and calculate IMT values. These imaging features are combined with related clinical information about patients and analyzed using the KNN algorithm to improve the accuracy of predictions. This framework is implemented using a Flask web interface that enables clinicians to upload images of ultrasound scans and obtain results quickly.

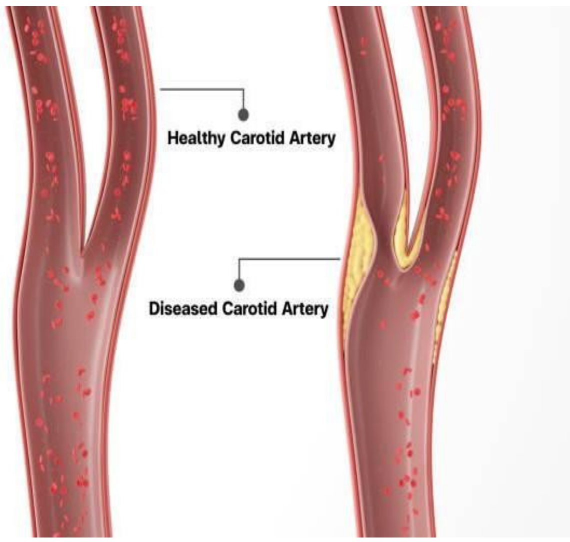

Fig.1 Carotid Plaque image

II. Related works

Murray Gabriela (2019) investigated the application of displacement variance measurements in detecting characteristics of human carotid plaques using a parameter called log(VoA). They investigated its effectiveness. From their findings, this parameter was found to be more effective than the conventional ARFI-induced peak displacement technique in differentiating between plaque components like lipid-rich necrotic core (LRNC), intraplaque hemorrhage (IPH), collagen, and calcium. It has also been found that this technique has a higher contrast-to-noise ratio and can be more effective in assessing stroke risks. [1]

Marie-Helene Roy-Cardinal et al. (2019) proposed a machine learning technique for classification of various carotid plaque constituents using homodyned K parametric maps and elastography. In this paper, various quantitative ultrasound features were used and analyzed using a random forest classifier. In this paper, good results were obtained for various plaque characterization problems with AUC ranging between 0.79 and 0.97. This paper also demonstrated that using various imaging features together can improve classification accuracy rather than using a single imaging technique. [2]

Frank J. H. Gijsen et al.(2021) examined how calcifications influence the biomechanical behavior and rupture risk of carotid plaques. Their study combined histological analysis with finite element modeling to better understand plaque structure. The results showed that the shape of calcifications and the arrangement of collagen fibers significantly affect stress distribution within plaque tissue. These findings provided useful insights into how calcification patterns are related to plaque instability. [3]

Chris L. de Korte et al. (2016) reviewed several techniques for evaluating the mechanical properties of carotid arteries and plaques. The study discussed ultrasound-based methods such as elastography, ARFI imaging, and shear wave imaging, along with CT and MRI techniques. The authors highlighted the importance of plaque composition analysis for predicting rupture risk, while noting challenges in routine clinical implementation.[4]

Gabriela Torres et al. (2020) investigated fibrous cap thickness measurement using the ARFI log(VoA) parameter. Their results showed stronger correlation with histological measurements compared to traditional ARFI peak displacement, indicating its usefulness for assessing plaque stability.[5]

Zhi Liu et al. (2019) evaluated the interoperator reproducibility of carotid elastography using ultrasound and MRI references. Their findings showed that elastography could identify vulnerable plaques with accuracy above 80%, demonstrating its reliability as a diagnostic technique.[6]

Luca Saba et al. (2021) performed a multicenter study applying six deep learning and machine learning models to characterize carotid plaque tissues. Their system, Atheromatic 2.0, achieved mean accuracies above 93% across multiple datasets and demonstrated superior performance compared to earlier versions. The study showed the scalability and stability of AI for large-scale carotid plaque classification.[7]

Karim Karim Lekadir et al. (2017) developed a convolutional neural network for automatic plaque composition detection in ultrasound images. Trained on about 90,000 annotated patches, the model achieved a correlation of 0.90 with expert assessments for identifying lipid core, fibrous tissue, and calcification.[8]

Keerthi S. Anand and colleagues (2023) compared focused-tracked and plane wave-tracked ARFI log(VoA) for imaging carotid plaques. Their results showed that plane wave tracking could improve imaging frame rate while maintaining performance in plaque characterization. The original imaging model for ARFI-based plaque imaging was plane strain imaging that uses an affine displacement model.[9]

From these studies, it can be observed how the analysis of carotid plaques has evolved gradually from conventional imaging and mechanical-based techniques to more sophisticated ARFI-based and AI-aided techniques. Although techniques like elastography and biomechanical analysis are beneficial in terms of providing structural information, more recent techniques involving machine learning and deep learning have been more accurate, efficient, and reproducible. This can be considered a good start in developing an integrated diagnostic framework, like the one proposed in the study, based on techniques like deep learning, segmentation, and clinical patient information to provide a more comprehensive evaluation.

The proposed system uses a combination of deep learning and machine learning methods to automatically detect carotid artery plaque, segment the affected region, and evaluate its severity. The overall methodology is divided into three main stages: plaque classification, plaque segmentation, and severity assessment. These stages work together within a single diagnostic framework and are implemented through a web-based interface for easier clinical use.

A. System Architecture

1. RESNET-50 for Plaque Classification

The ResNet-50 architecture is selected because of its residual learning design, which uses shortcut connections to allow information to pass across layers more effectively. This structure helps address vanishing gradient issues and enables the network to learn deeper feature representations while maintaining efficient training, even with limited medical imaging datasets. The model is trained to identify the presence or absence of plaque in carotid ultrasound images by detecting subtle variations in the arterial wall that may indicate early-stage atherosclerosis.

The classification output provides a confidence score indicating the likelihood of plaque presence, allowing clinicians to focus on images that require further examination and detailed analysis.

2. UNet-based Segmentation for IMT Measurement

Precise segmentation of the intima and media layers is essential for assessing the condition of the arterial wall. The U-Net model utilizes an encoder–decoder architecture with skip connections, enabling accurate pixel-level segmentation and producing detailed maps that clearly indicate plaque regions.

The estimated Intima–Media Thickness (IMT) acts as a quantitative biomarker and is widely used in clinical practice as an early indicator of potential cardiovascular risk.

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3. K-Nearest Neighbors (KNN) for Severity Estimation

The KNN model combines image-based features obtained from ResNet-50 and U-Net with patient clinical information such as age, gender, blood pressure, cholesterol level, and lifestyle factors. By analyzing similarities between patient profiles, the KNN algorithm generates an overall plaque severity score and classifies patients into different risk levels, including mild, moderate, or severe. This method allows the evaluation to consider both structural changes in the artery and important clinical parameters, resulting in a more personalized risk assessment.

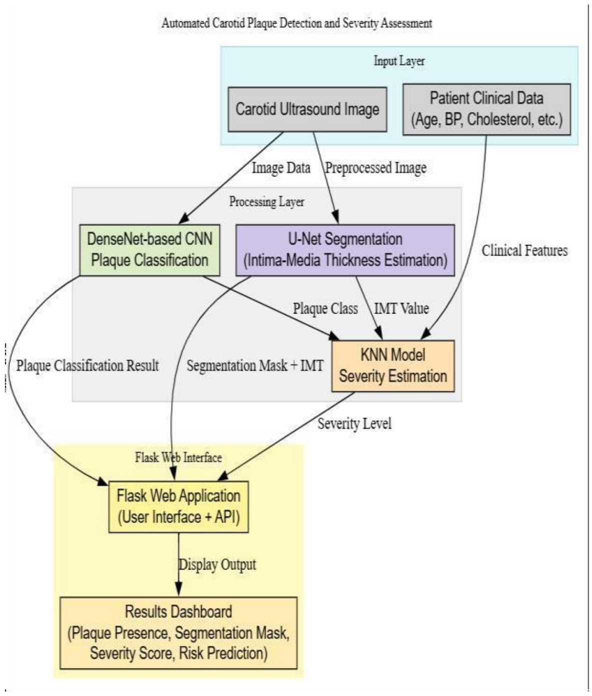


Fig.2 System Architecture Diagram

B. Proposed Design

Our system has great relevance towards clinical practice. It provides a very high accuracy of diagnosis of a person. So, tests provide a clearer interpretation. How our system works.

1. Data Acquisition:

Carotid Ultrasound Images: High-resolution B-mode Ultrasound images are collected and used as the main input for the automated detection and segmentation of carotid plaque. In addition, patient clinical data—including demographic details, medical history such as hypertension and diabetes, as well as lifestyle factors and laboratory results—are incorporated to improve the accuracy of plaque severity assessment.

a) Normalization:

Adjusts pixel intensity values to maintain consistent image contrast across all ultrasound images.

b) Noise Reduction:

Gaussian filters are applied to reduce is noise in the images.

1. Data Augmentation:

Methods such as rotating, flipping and adjusting brightness are used to increase the diversity of the dataset and help the model generalize better.

2. Plaque Classification:

The preprocessed images are then passed through the ResNet-50 model, and the model makes a prediction on the presence of the plaque and returns a confidence score for the prediction. This classification ensures that the segmentation and severity analysis of the images are carried out only on relevant images.

3. Segmentation and IMT Calculation:

Images where plaque is detected are then processed using a U-Net–based segmentation model. This step helps identify the inner and outer boundaries of the arterial wall and marks the plaque regions in the image. Using these segmented layers, the intima–media thickness (IMT) is measured.

4. Severity Estimation:

In the final stage, the output produced by ResNet-50 and U-Net, along with the clinical data of the patient, is given to the KNN model as input. The KNN algorithm recognizes the severity of the patient based on the patterns of similar patients in the past. It categorizes patients into a low risk moderate risk high risk based on the risk assessment score. The informed further by patient clinical data facilitates a more thorough analysis of findings.

5. Visualization and Reporting:

a) The Flask interface presents:

1. Plaque classification results
2. 2. Segmentation maps that clearly show the detected plaque regions
3. IMT measurements
4. Severity scores along with classification into different risk levels.

According to clinical literature, a critical illness said to cause worse outcomes among individuals. The outcomes suffering from delirium includes a longer hospital stay the higher rates of institutionalization and more serious cognitive impairment.

6. System Robustness and Validation:

To test the framework level testing of each model i.e. (RESNET-50, UNet, and KNN) unit testing is done. Integration testing is performed on the.

I. Results & Evaluation

The dual deep learning system developed for detecting carotid artery plaque and assessing its severity was thoroughly evaluated and showed high accuracy and reliable performance.

a) Plaque Classification (RESNET-50):

The system showed high sensitivity and specificity in detecting the presence of plaque, confirming its ability to recognize subtle patterns in ultrasound images..

b) IMT Segmentation (UNet):

The model accurately segmented the intima–media layers, enabling reliable quantitative measurements of plaque severity, with high performance and reflected in metrics.

c) Severity Estimation (KNN):

The system effectively combined imaging features with patient clinical data to classify plaque severity.

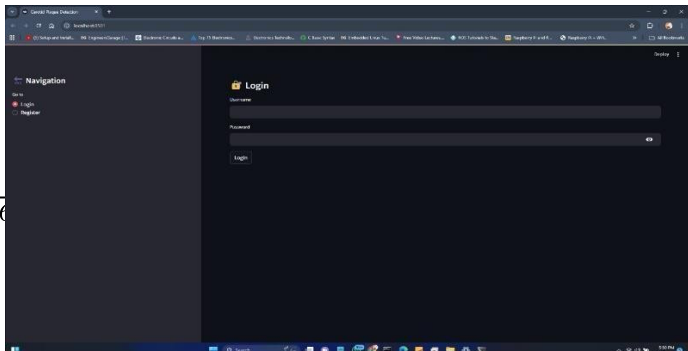
d) System Integration:

The Flask-based web interface was able to effectively connect all the models, thus allowing smooth data processing. User acceptance and stress testing of the system confirmed that it was stable and easy to use.

e) Generalizability:

When tested on diverse datasets, the system demonstrated strong adaptability across different patient populations.

Fig.3 Login page



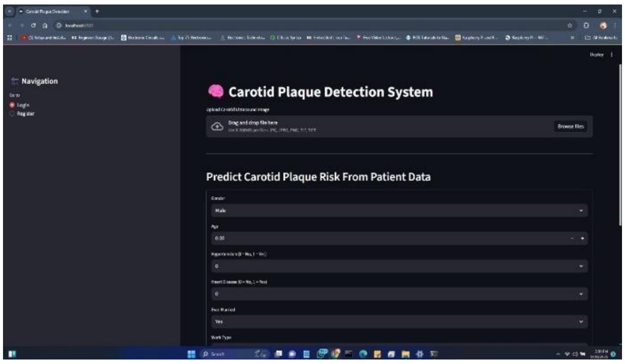


Fig.4

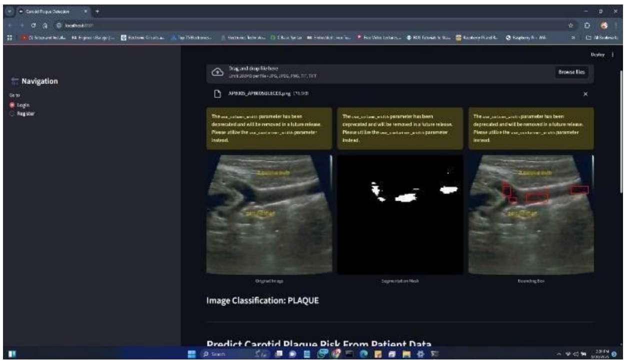


Fig.5

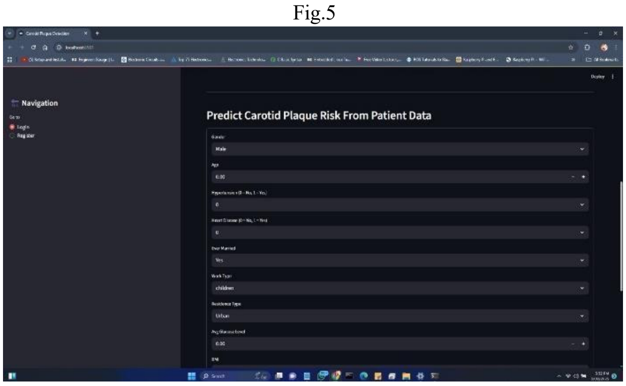


Fig.6

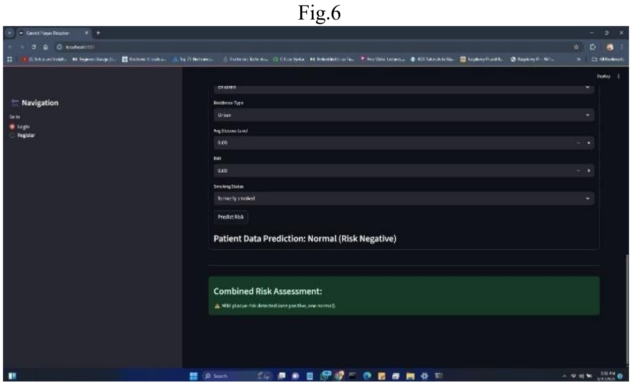


Fig.7

II. Conclusion

This project effectively created an automated, accurate, and complete carotid artery plaque detection and severity measurement system. Using RESNET-50 for classification, UNet for segmentation of IMT, and KNN for multi-modal severity estimation in a Flask web interface easy to use by users, the system improves upon classical approaches. It improves diagnostic accuracy, diminishes dependency on operators, and offers timely and consistent insights to clinicians. This development is pivotal to early intervention, eventually leading to the prevention of stroke and better

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