Preface for a Special Issue of AUDT with AI in Medical Ultrasound

Invited Editors

In recent years, the continuous development of AI technology has led to the emergence of many new ultrasound technologies based on artificial intelligence, greatly promoting the development of ultrasound medicine. Advanced technologies such as ChatGPT and 5G have ushered in a new era of innovation in the field of ultrasound medicine, offering new possibilities for digital intelligence.

The potential applications of ChatGPT in ultrasound have been discussed and hotly debated by Chinese scholars. This discussion has also been of great interest to our Editor-in-Chief, Ji-Bin Liu, who suggested a special issue on ultrasound AI and ChatGPT-related ultrasound applications, leading to the creation of this issue. Undoubtedly, ultrasound medicine will undergo significant upgrades and improvements, providing doctors with even more advanced tools and methods to aid in the diagnosis and treatment of diseases.

As ChatGPT comes online, the Advanced Ultrasound in Diagnosis and Therapy (AUDT) has collaborated with leading experts in the field of ultrasound medicine and artificial intelligence to release a special issue in both print and online formats. This special issue will focus on the application of AI, ChatGPT and 5G technologies in ultrasound medicine, and will feature review articles on the current status and trends in ultrasound medicine technology. We hope to provide leading-edge knowledge and useful information for both clinical researchers and basic scientists.

The Advanced Ultrasound in Diagnosis and Therapy (AUDT) is an open access journal in English with both online and printed publications which was created by the China-American Ultrasound Scholar Alliance. The journal covers various topics related to ultrasound technology, including advanced ultrasound imaging techniques, ultrasound-guided interventions, and the development of new ultrasound technologies. This special issue will introduce the application progress and prospects of AI in advanced ultrasound technologies, such as modality conversion, 3D/4D reconstruction, semi-supervised ultrasound video object segmentation (SUVOS), automated breast volume scanning (ABVS) and cloud handheld ultrasound system. Due to the large number of articles received in this special issue, some of them will be published in the upcoming issue.

We express our sincerest gratitude to all the members of the editorial board, journal reviewers, and authors for their diligent efforts in contributing to this journal and producing exceptional articles within a limited time frame. We also extend our appreciation to all the experts, scholars, and readers for their support and interest in this special issue of the journal. We welcome any feedback and comments on the content of this issue, which we hope will provide practical value and assistance to our readers.
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Rapid Screening of Carotid Plaque in Cloud Handheld Ultrasound System Based on 5G and AI Technology

Wenjun Zhang, MD a, Mi Zhou, PhD a, Qingguo Meng, MD a, Lin Zhang, MS b,*, Xin Liu, MS c, Paul Liu, PhD c, Dong Liu, PhD a,e

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Objective: To evaluate the real-time accuracy of cloud handheld ultrasound system using AI technology in screening carotid plaque.

Methods: 2627 ultrasound images of the carotid artery are collected using the cloud handheld system. Bounding boxes of carotid plaques are labeled by qualified sonographers, and the dataset is trained using a lightweight YOLOv3 model. An additional and separate 390 images are collected and tested using the evaluation metrics average recall (AR), average precision (AP), and frames per second (FPS) for quantifying classification performance and time consumption.

Results: We use a plaque grading definition with a thickness of 1.2-1.5 mm defined as small plaque, 1.5-3 mm as medium plaque, and more than 3 mm thick as large plaque. Our model achieves \( AP_{IoU=0.50} \) with 96.5%, \( AP_{large} \) is 79.9%, \( AP_{medium} \) is 90.7%, \( AP_{small} \) is 93.5%; \( AR_{IoU=0.50} \) is 64.5%, \( AR_{large} \) is 60.6%, \( AR_{medium} \) is 58.3%, \( AR_{small} \) is 70.8%, and FPS is 33.3.

Conclusion: We establish a framework for data set construction, model selection, training, and testing of carotid ultrasound images and verify the effectiveness of real-time AI technology in the automatic detection of carotid artery plaque.

Key words: Handheld ultrasound; Carotid plaque; YOLOv3; Artificial intelligence (AI)

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Cardiovascular disease is the leading cause of death worldwide, and stroke is a significant source of cardiovascular disease burden as it requires immediate treatment to prevent brain injury, disability, or death. There are different types of stroke, such as ischemic stroke caused by thrombosis, hemorrhagic stroke caused by cerebral hemorrhage, and transient ischemic attack caused by temporary blockage.

An important but clinically detectable source of blockage is carotid plaque, which is a buildup of fatty deposits (plaques) in the carotid arteries that supply blood to the brain and head. Carotid plaque can increase the risk of stroke by reducing blood flow to the brain or by breaking off and traveling to smaller cerebral arteries causing blockage. Early detection of carotid plaque is important to prevent stroke and other complications because carotid plaque formation is a gradual progressive condition with no symptoms in early stages. Vulnerable plaques with the potential to break off is especially important to detect with different imaging techniques [1-2].

Among the many methods of medical imaging [3], including magnetic resonance angiography (MRA), computerized tomography angiography (CTA), and cerebral angiography, carotid ultrasound has the...
advantages of being safe, noninvasive, and real-time and providing superior spatial and contrast resolution. Ultrasound can image the blood flow through the carotid arteries, estimate the thickness of the artery wall, and detect the anatomical type of plaques or clots.

However, manual identifying and outlining of plaques by doctors is time-consuming and potentially inaccurate due to variations of the scan planes among different frames, system noise, and acoustic artifacts, especially reverberation. In [4], artificial intelligence (AI) is compared with the conventional or non-AI-based methods and demonstrates excellent performance in various domains of medical images, more time-effective solutions, and stronger economic benefits [5] as the training of qualified sonographers is an expensive and time-consuming process. AI algorithms have changed the landscape of cardiovascular disease risk assessment and demonstrate better performance when compared against conventional models [6-8], and the study in [9] reviews the modern automated methods using artificial intelligence. The aim of this study was to introduce and evaluate the novel method by screening carotid plaques based on AI for automatic diagnose in order to improve the prevention and control of cardiovascular disease.

Patients and Methods

Patients

From May 2022 to March 2023, our team conducted free screening activities in communities where high-risk elderly groups gathered in Chengdu, and we obtained a total of 2979 images. Only positive cases, i.e. plaque is present, result in saved images. Multiple images may be saved for each positive person. After manual evaluation, the total positive rate of plaques is 50.54% for all scanned subjects. Table 1 shows the distribution of positive cases by age group. We find that in people over the age of 50, the risk of carotid plaque sharply increases.

<table>
<thead>
<tr>
<th>Years</th>
<th>0-40</th>
<th>40-50</th>
<th>50-60</th>
<th>60-70</th>
<th>70-80</th>
<th>80-90</th>
</tr>
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<tbody>
<tr>
<td>&lt;1.5 mm</td>
<td>1.95</td>
<td>2.6</td>
<td>9.51</td>
<td>8.33</td>
<td>7.81</td>
<td>2.86</td>
</tr>
<tr>
<td>&lt;2 mm</td>
<td>0.26</td>
<td>0.23</td>
<td>3.52</td>
<td>2.34</td>
<td>2.99</td>
<td>2.34</td>
</tr>
<tr>
<td>&lt;3 mm</td>
<td>0</td>
<td>0.13</td>
<td>0.52</td>
<td>0.78</td>
<td>1.17</td>
<td>0.78</td>
</tr>
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Instruments and Materials

In recent decades, life expectancy has increased, but the incidence rate of stoke has also increased, lowering the quality of elderly life. In China, the challenges preventing large-scale screening and regular return visits even for high-risk groups include a shortage of qualified ultrasound physicians, imperfect diagnosis, and difficulty in moving conventional ultrasound equipment to geographical scanning locations that may be distant from hospitals or clinics.

In response to such difficulties, Stork Healthcare proposes a cloud handheld ultrasound series as shown in Fig. 1. The ultra-portable 64 digital channel system is a wireless scanner that includes linear, convex, and phased array geometries for the scanning of peripheral anatomy, abdominal parts, and the heart respectively. For the carotid application, we use the linear probe geometry at center frequency of 8.5 MHz. Retrospective focusing in the beamforming process is used to increase image quality.

Figure 1 Cloud handheld scanning equipment. Linear, convex, and phased array geometries are available for the scanning of peripheral anatomy, abdominal parts, and the heart respectively.

The overall software processing architecture consists of the following: patients are first registered online using a separate app which is connected to the ultrasound scanner server-side via the cloud; then real-time AI is run on the local device using the device graphical processing unit (GPU); finally the AI results of selected frames
are manually uploaded by the scanner operator into
the cloud. Severe and/or difficult cases are viewed and
diagnosed asynchronously from the cloud by doctors of
the Chengdu City Wenjiang District People’s Hospital.
Fig. 2 shows the main workflow of the system.

Previously reported algorithms are mostly used for
image segmentation of positive cases, and do not meet
the requirements of rapid screening which is a real-time
detection problem. For this problem, we use a modified
YOLOv3 [10] model, which is a deep convolutional
neural network, to learn features of the input image
and to output labeled bounding boxes with their plaque
probabilities. The lightweight model, which we call
Tiny-YOLOv3, is deployed on the GPU of a Qualcomm
Snapdragon 865 processor using Tensorflow Lite. The
real-time results are used to quickly screen out the
positives and the negatives and to determine whether
doctor assistance is required for further diagnosis. This
process significantly reduces the proportion of negative
cases that require expert viewing.

![Figure 2](image)

**Figure 2** Cloud handheld ultrasound work flow. Patients are registered online and then scanned. The on-device AI screens for potential positives, which are then manually uploaded for further inspection and diagnosis.

![Figure 3](image)

**Figure 3** (A) Single plaque in the common carotid artery; (B) Multiple plaques (anterior and posterior) in the common carotid artery.

Since YOLOv3 require manual tracings to train the
neural network, rectangular bounding boxes are used
to trace all plaques, which we define as regions where
intima thickness exceeds 1.2 mm, as shown in Fig. 3.
Differences between ultrasound images and ordinary
images make it possible to reduce the size of the Yolov3
model. Because ultrasound images are grayscale, input
is a single channel. In most cases, the number of carotid
plaque is only one; even if there are multiple plaques,
empirically the number rarely exceeds five. Therefore,
we reduce the number of all filters in the Darknet-53
to 1/4 of the original number; similarly, the number of
filters in the upper sampling layers is reduced to 1/8 of
the original [10]. We call the reduced size model Tiny-
Yolov3.

Because most of our devices are used outdoors,
doctors may frequently adjust the gain due to the
influence of light, which can reduce the accuracy of AI
results. Therefore, in our system, the gain of images ‘seen’
by doctors is adjustable, while the gain of images ‘seen’
by AI is fixed. Before training and testing, the images
need to be normalized in grayscale.

**Results**

We randomly divided the collected images into
2589 training set data and 390 test data, and train using
120 epochs. Our problem is different from traditional
detection problems in that labeled or detected plaques
enclosed by separate bounding boxes using our rule of
intima greater than 1.2 cm may in fact physically be the
same plaque. Fig. 5 illustrates this issue in that a large
labeled mixed-echoic plaque may result in prediction of
two boxes, consisting of a hyperechoic harder component...
and a hypoechoic softer component, both of which may independently show up as individual plaques in our data set. However, from a detection perspective, successfully detecting the components separately still should count as a successful overall detection. Because most of our dataset consists of smaller plaques, i.e. < 3 mm, detection of components occurs quite frequently.

Thus, we define the union of the ground truths as $GT_U = \bigcup_{i=1}^M GT_i$ and the union of the predicted results as $Pred_U = \bigcup_{i=1}^N Pred_i$. We then calculate the intersection over union (IoU) of $GT_U$ and $Pred_U$ as $\text{IoU}_{GTU} = \frac{GT_U \cap Pred_U}{GT_U \cup Pred_U}$.

Each image is mapped to a binary decision, representing a positive case where plaque exists and a negative case where plaque does not exist. We determine positive and negative cases with different thresholds $T$ where $\text{IoU}_U > T$ denotes a positive case. We then calculate evaluation indicators such as AP and AR based on these results. Performance deteriorates noticeably as the IoU threshold rises in Table 2, indicating that YOLOv3 has difficulty in matching the boxes precisely with the object. In our screening application, $AP_{\text{IoU} = 0.5}$ and $AR_{\text{IoU} = 0.5}$ are more suitable indicators because it is not necessary to output precise coordinates. With the increase of IoU, especially for small plaques, AR decreases even more severely. This means that the prediction and GT of small plaques overlap less.

<table>
<thead>
<tr>
<th>Area</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
<th>All</th>
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<tr>
<td>$AP_{\text{IoU} = 0.5}$</td>
<td>68.6</td>
<td>67.0</td>
<td>53.8</td>
<td>78.6</td>
</tr>
<tr>
<td>$AR_{\text{IoU} = 0.5}$</td>
<td>29.4</td>
<td>27.2</td>
<td>29.2</td>
<td>28.5</td>
</tr>
<tr>
<td>$AP_{\text{IoU} = 0.75}$</td>
<td>93.5</td>
<td>90.7</td>
<td>79.9</td>
<td>96.5</td>
</tr>
<tr>
<td>$AR_{\text{IoU} = 0.75}$</td>
<td>70.8</td>
<td>58.3</td>
<td>60.6</td>
<td>64.5</td>
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<tr>
<td>$AP_{\text{IoU} = 0.75}$</td>
<td>77.2</td>
<td>66.6</td>
<td>61.5</td>
<td>87.4</td>
</tr>
<tr>
<td>$AR_{\text{IoU} = 0.75}$</td>
<td>16.5</td>
<td>11.9</td>
<td>24.2</td>
<td>15.9</td>
</tr>
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Discussion
Stroke prevention and treatment in China is facing
enormous challenges. In 2018, the mortality rate of cerebrovascular diseases in China was 149.49/100000 [11], resulting in 1.57 million deaths, including 164.31/100000 for males and 134.15/100000 for females. Moreover, patients are increasing at a rate of 8.7% annually. In spite of the high morbidity, stroke is preventable and controllable. Through active measures, the death rate of stroke in the United States in 2007 was 35% lower than that in 1990, the incidence rate of men in the United States in 2006 was 30% lower, and the incidence rate of women was 18% lower.

China’s population growth rate is relatively slow, with an annual average growth rate of 0.53%. However, the number of patients with cerebrovascular diseases in China is increasing at an annual rate of 8.7%, indicating that the pathogenic factors and key factors of cerebrovascular diseases have not been effectively controlled, and still causes a large number of undesired deaths and disabilities in China. The lack of screening and prevention means makes it difficult to achieve prevention and control. The lack of extensive, rapid, and effective screening methods is one of the reasons for the above problems.

In the 1990’s, computer-assisted image processing is firstly used to analyze ultrasound images of carotid plaques and to measure them in [12]. Later, computer-assisted processing is widely used in the analysis of image grayscale and plaque properties [13-16]. Principal component analysis (PCA) and support vector machine (SVM) [17-18] from machine learning are used to analyze the relationship between carotid plaques and stroke. Since the 2010’s, deep learning has made significant breakthroughs in various fields such as computer vision, especially convolutional neural networks (CNNs) [19] in image classification. Early available applications of carotid plaque imaging include magnetic resonance imaging (MRI) classification [20]. Later, deep residual nets (ResNets) [21] are used to automatically extract features of carotid ultrasound images and identify the plaques in the images [22], and CNNs variants are also used for plaque tissue classification and characterization [23-25]. With the emergence of U-Net [26], the popular application of AI in carotid plaque has turned to image segmentation [27-33].

Although AI has achieved many results in outlining the shape of the carotid artery, we believe that detection is the first step in prevention and control. Considering the accuracy and speed of YOLOv3 in target detection field, we introduce it into our rapid screening system for carotid plaques. Our results showed the identification rate of YOLOv3 in detecting carotid plaques was as high as 96.5%. Intuitively, large plaques should be easier to identify than small plaques, but in our results, $AP_{IoU = 0.50}$ of small plaques is 93.5%, while $AP_{IoU = 0.50}$ of large plaques is only 79.9%, caused by data unbalance. Data source is from communities rather than hospitals caused lower proportion of large plaques. Another noteworthy factor is the mutation in the recall rate. In practical, doctors rely solely on experience to measure plaques, which can easily lead to missed plaques near 1.2 mm and cause network confusion. The small plaque itself is defined around 1.2 mm, so it is most affected (16.5%); In the middle, large plaques are generally hilly in shape, although the central uplift height is much thicker than 1.2 mm, there are also thickness near 1.2 mm on both wings, which can lead to a decrease in IoU caused misjudgment. Therefore, the $AP_{IoU = 0.75}$ of all plaque types has sharply decreased (15.9%).

This provides accurate box for outlining the appearance of plaque in next step. Compared to traditional big data, medical imaging datasets can only be considered 'small data', and due to the protection of patient privacy, they are scattered in various hospitals, which further exacerbates the difficulty of collection. AI in the field of medical imaging may be in a long-term situation where the smaller the dataset, the higher the uncertainty of the results, and the lower the credibility of AI. YOLOv3 precisely provides an uncertainty, and by utilizing this feature, we can also treat the detected targets separately.

In conclusion, the cloud handheld system has the following advantages for the application of rapid screening of carotid plaque. Firstly, it can effectively and extensively screen vascular plaque at a low cost. Secondly, it can identify vulnerable patients as early as possible. Finally, effective methods of classifying patients reduce the likelihood of excessive medical problems or high emergency medical costs. Incorporating early screening work into the community is an effective way to prevent and control cardiovascular disease, and sustainable regular return visits can also alleviate the urgent demand for medical resource.

Conflict of Interest
Lin Zhang, Xin Liu, and Paul Liu are employees at Stork Healthcare.

References


