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TECHNICAL NOTE

Automatic Detection of Visceral Arterial Aneurysms on Computed Tomography Angiography Using Artificial Intelligence Based Segmentation of the Vascular System

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Introduction: Visceral arterial aneurysms (VAAs) are life threatening. Due to the paucity of symptoms and rarity of the disease, VAAs are underdiagnosed and underestimated. Artificial intelligence (AI) offers new insights into segmentation of the vascular system, and opportunities to better detect VAAs. This pilot study aimed to develop an AI based method to automatically detect VAAs from computed tomography angiography (CTA).
Methods: A hybrid method combining a feature based expert system with a supervised deep learning algorithm (convolutional neural network) was used to enable fully automatic segmentation of the abdominal vascular tree. Centrelines were built and reference diameters of each visceral artery were calculated. An abnormal dilatation (VAAs) was defined as a substantial increase in diameter at the pixel of interest compared with the mean diameter of the reference portion. The automatic software provided 3D rendered images with a flag on the identified VAA areas. The performance of the method was tested in a dataset of 33 CTA scans and compared with the ground truth provided by two human experts.
Results: Forty-three VAAs were identified by human experts (32 in the coeliac trunk branches, eight in the superior mesenteric artery, one in the left renal, and two in the right renal arteries). The automatic system accurately detected 40 of the 43 VAAs, with a sensitivity of 0.93 and a positive predictive value of 0.51. The mean number of flag areas per CTA was 3.5 $\pm$ 1.5 and they could be reviewed and checked by a human expert in less than 30 seconds per CTA.
Conclusion: Although the specificity needs to be improved, this study demonstrates the potential of an AI based automatic method to develop new tools to improve screening and detection of VAAs by automatically attracting clinicians' attention to suspicious dilatations of the visceral arteries.

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INTRODUCTION

Visceral arterial aneurysms (VAAs) are a rare entity, and they represent approximately 5% of all intra-abdominal aneurysms.[1,2] VAAs are life threatening and pose a risk of rupture associated with a high mortality rate.[1,3,4] They are often asymptomatic and are increasingly diagnosed on incidental findings on imaging.[1—3] However, due to the paucity of symptoms and rarity of the disease, VAAs remain underdiagnosed and underestimated. Artificial intelligence (AI) has brought new insights into medical imaging analysis and has offered new opportunities for the diagnosis of a wide range of cardiovascular diseases, including cardiac diseases, aortic pathologies, cerebrovascular diseases, carotid stenosis, as well as peripheral artery disease.[5—7] Among machine learning (ML) algorithms, convolutional neural network (CNN) is one of the most commonly used techniques. Previous studies have demonstrated its potential to enhance vascular imaging segmentation, to enable characterisation and automatic detection of arterial aneurysms.[8—11] While the use of CNN to diagnose aortic aneurysms has been

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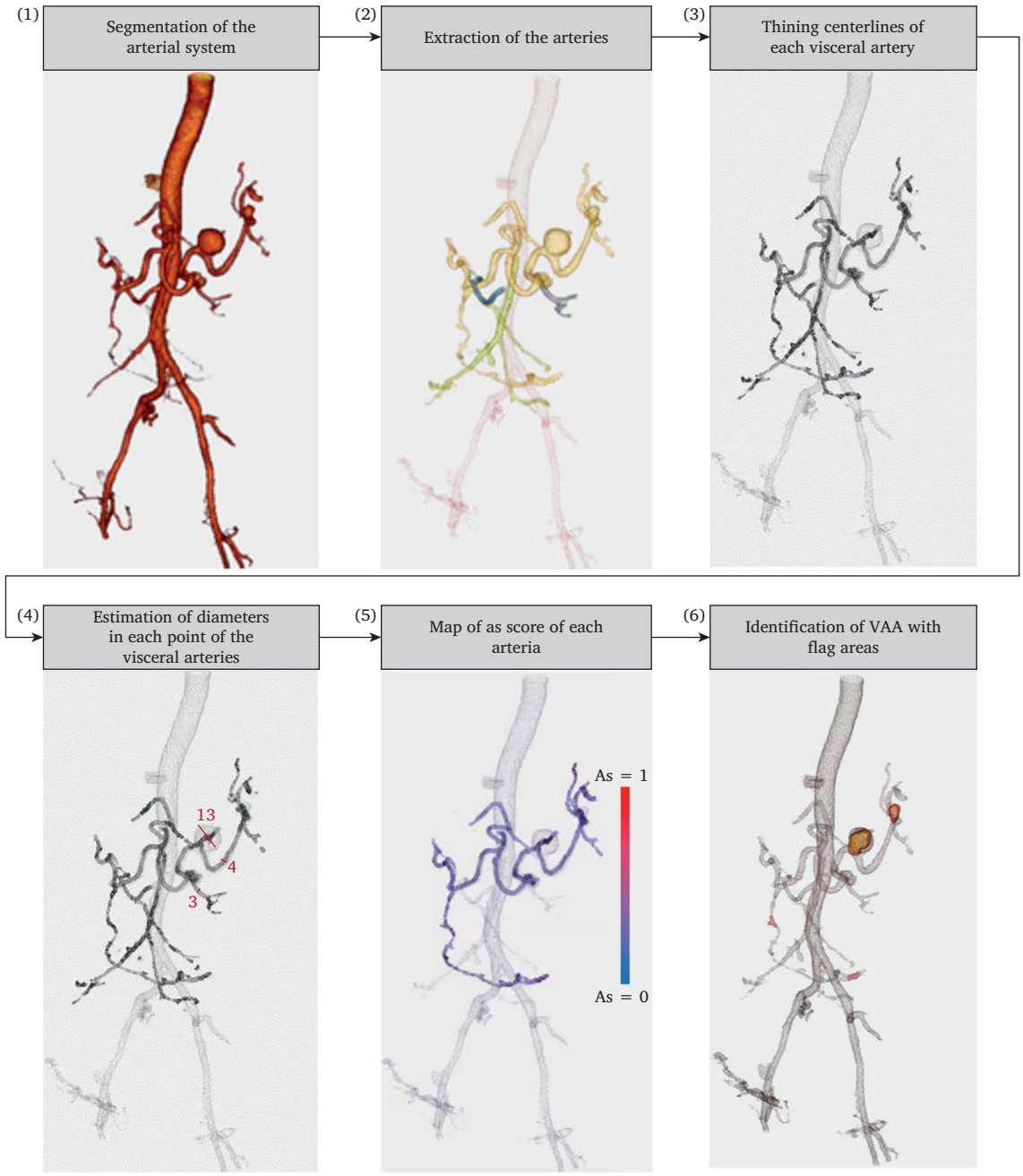

Figure 1. Pipeline used for automatic detection of aneurysms of the visceral arteries. (1) The abdominal arterial system is segmented using a hybrid method combining an expert system with supervised deep learning. (2) The visceral arteries are extracted by subtracting the abdominal aorta and the iliac arteries. (3), (4) The centrelines are built and the diameters of the visceral arteries are calculated. (5) A multimodal approach is used to identify areas with abnormal dilatations (visceral artery aneurysm, VAAs). (6) VAAs are automatically detected with flag areas (in red) and 3D images are extracted.

reported previously, AI driven approaches to detect VAAs have not been investigated so far. The present authors hypothesise that such methods could be transposed to identify dilatation of the visceral arteries and automatically detect VAAs from computed tomography angiography (CTA).

SURGICAL TECHNIQUE

The abdominal arterial system was segmented using a hybrid method combining a feature based expert system with a supervised deep learning (DL) algorithm as published previously (Fig. 1).[9,10] The visceral arteries were then extracted using the following steps (Fig. 1): the abdominal aorta, identified as the main ascending tubular structure, was subtracted from the 3D volume of the abdominal arterial system; the same method was then applied to subtract the iliac arteries. Each independent 3D component of the resulting level set with a notable volume was extracted as an artery. Components with volume $<1\,000$ pixels were ignored.

Visceral arteries' centrelines were built using a thinning method and the diameters of each visceral artery were

measured given the centreline (Fig. 1). To identify arterial dilatation, the diameters of the visceral artery were compared with the reference diameter of the artery (Fig. 2). The reference diameter $\delta_{ref}\ (i)$ of the artery portion was evaluated on a reference tubular portion around pixel i according to the formula:

$$\delta_{ref}(i) = \frac{1}{2\,l}\left[\sum_{j=i-\Delta-l}^{i-\Delta}\delta_j + \sum_{j=i+\Delta}^{i+\Delta+l}\delta_j\right]$$

Two parameters were used to define the portion used to compute the reference diameter (Fig. 2): - Δ (mm), corresponding to the distance between the pixel of interest and the beginning of the reference portion, - l (mm) defined as the length of the tubular portion the diameter of which will be averaged to obtain the reference diameter. δ_j refers to the diameter measured at pixel j.

An abnormal arterial dilatation *As* was defined as an arterial diameter superior to ρ times the reference diameter. In other words, ρ is the minimum percentage of local dilatation of visceral artery that indicates a risk of aneurysm:

$$As(i) = \begin{cases} True\ if\ \delta_i \geq \rho\ .\ \delta_{ref}(i) \\ False\ if\ \delta_i < \rho\ .\ \delta_{ref}(i) \end{cases}$$

A multimodel approach was used to select parameters with the best performance to identify VAA depending on the shape of the aneurysms. The model runs with combinations of l and Δ. Each pixel is associated with an anomaly score computed through:

$$As(i) = \frac{1}{card(\Delta).card(l)}\sum^{\Delta}\sum^{l} As_l^{\Delta}(i)$$

The score takes values between 0 and 1: 0 meaning all models simulate this pixel as normal, and 1 all models simulate this pixel as a part of a dilatation anomaly. An anomaly with *As (i)* $>$ 0.33 was considered to be an area with VAA.

Numerical insights were provided from the pipeline with automatic calculation of mean, maximum, minimum diameters, and volume of the arterial portions with dilatation. A visualisation of the 3D rendered images of the arterial system was provided with a coloured flag highlighting the areas where a VAA was automatically detected.

The performance of the method for automatic detection of VAAs was tested in a dataset of 33 computed tomography angiography (CTA) scans. The dataset was collected retrospectively from patients diagnosed with a VAA in several hospital centres in France. It included patients admitted to the hospital for treatment of VAA as well as incidental findings on imaging. Only patients for whom a CTA (DICOM format) was available with arterial phase acquisition were included. The CTAs were provided from four different manufacturers and the mean pixel size and slice thickness were, respectively, 0.79 $\pm$ 0.09 mm and 0.86 $\pm$ 0.38 mm. Two human experts analysed the CTAs and manually annotated areas where they diagnosed a VAA. They identified 43 VAAs, among which 32 were located in the coeliac trunk branches, eight in the superior mesenteric artery and three in the renal arteries. Among the 43 VAAs, 20 (46.5%) were fusiform and 23 (53.5%) saccular. The automatic system accurately detected 40 of the 43 VAAs, which corresponded to a sensitivity of 0.93. Representative images of the accurate detection of the VAA by the automatic method are provided in Figure 3. The three cases for which the automatic method failed to identify the VAA included two thrombosed aneurysms and one aneurysm in which a coil was present in the proximal part that hindered the detection. A total of 101 flags was identified by the automatic method within the abdominal vascular tree, among which 52 were located in the VAA, corresponding to a positive predictive value of 0.51. The mean number of flag areas per CTA was 3.5 $\pm$ 1.5 and the computational time for a human expert to check the flag areas generated by the automatic method was quick (within 30 seconds).

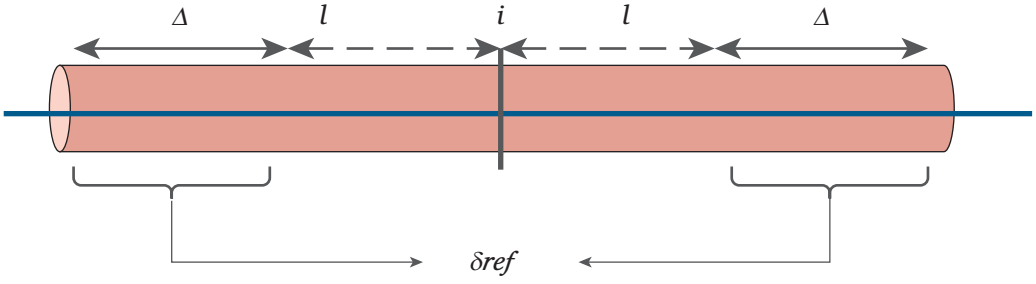

Figure 2. Illustration of the method used to compute reference diameters and identify areas with arterial dilatation. The reference diameter *δref (i)* is the average expected diameter at point *i* if no aneurysm is present at position i. *δref (i)* is evaluated on a reference tubular portion around pixel *i*. *l* designates the range of artery portion close to *i* excluded from the calculation of the reference diameter. *Δ* is the width of the portion of artery before *i-l* and after *i+l* used to compute the reference diameter around position *i*. If diameter at *i* is $>$ ***ρ*** times the reference diameter *δref (i)*, point *i* is identified as abnormal. A multimodel approach runs with the combination of *l* and *Δ*. If at least 33% of the couples of values of *l* and *Δ* identify *i* as abnormal, it is classified as a visceral artery aneurysm (VAA) and identified with a flag area.

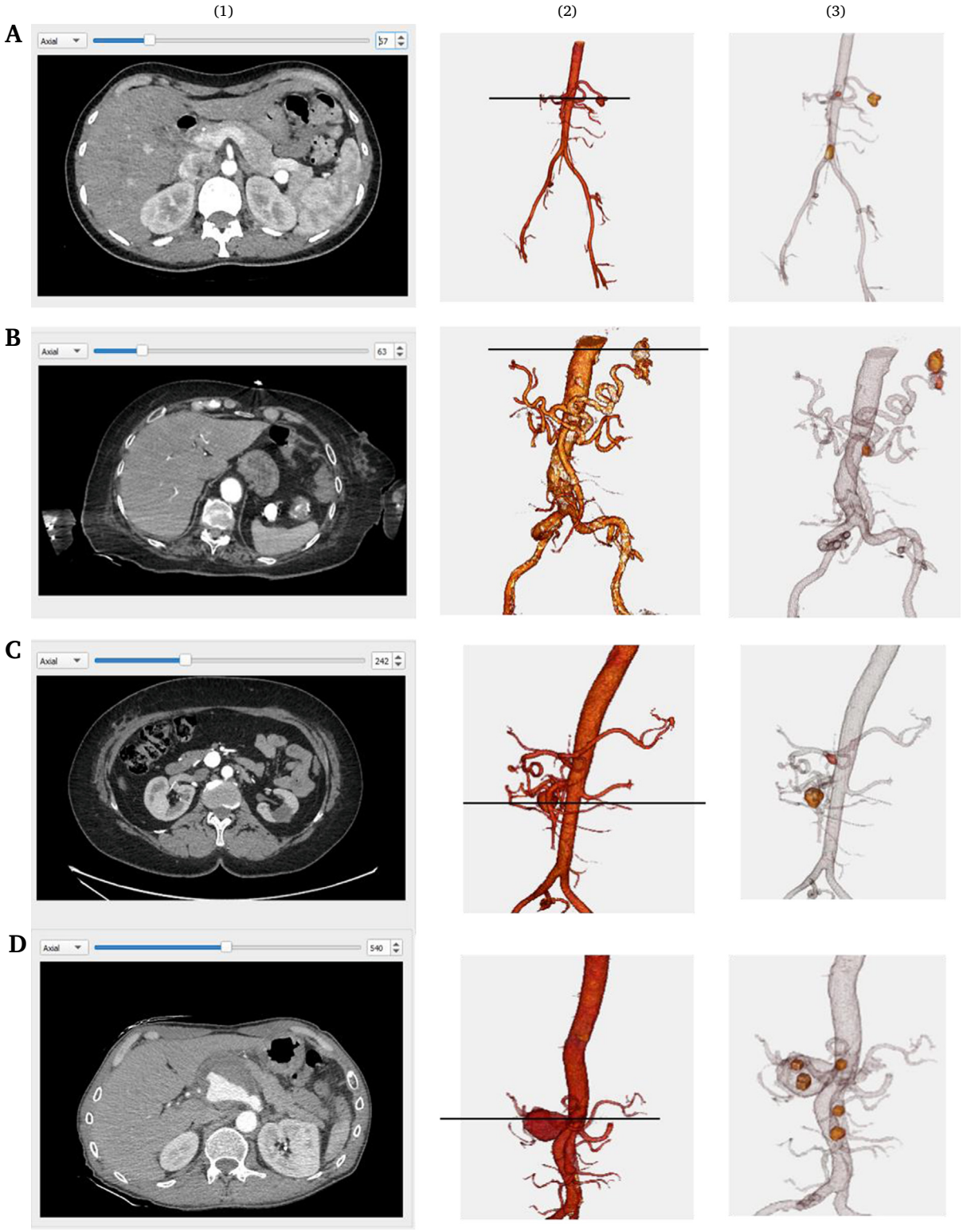

Figure 3. Representative examples of identification of visceral arterial aneurysms (VAAs) using the automatic method. (1) Raw images from computed tomography angiography (CTA). (2) 3D images. (3) Flag areas identifying VAAs using the automatic method. (A), (B) Aneurysms in the coeliac trunk branches. (C), (D) Mesenteric aneurysms.

DISCUSSION

This pilot study proposes an innovative method to identify abnormal dilatations of the visceral arteries and automatically detect VAAs on CTA. Although the specificity needs to be improved, the automatic method provided fast detection of VAA with high sensitivity. The identified suspicious arterial areas could then be easily and quickly checked by human experts to confirm or not the diagnosis of VAA.

Over the past decades, both advances in imaging techniques and endovascular treatments have improved the opportunities for clinicians to identify asymptomatic VAAs and propose therapeutic interventions in cases with complex anatomical lesions.[1] Despite these technological improvements, VAAs are still underdiagnosed and undertreated. Early identification of the disease is of utmost importance to enhance patient survival by offering opportunities to prevent and anticipate complications through careful evaluation of therapeutic options, pre-surgical planning, and elective treatment when indicated in accordance with current guidelines.[1,2] The results of this study underline the interest in AI driven approaches for development of screening tools that could help in detection and diagnosis of VAAs. This could contribute to enhance incidental findings on CTAs.

While this pilot study is a proof of concept, there are several limitations. The dataset collected was relatively small and the method needs to be tested in larger cohorts to confirm its ability to identify VAAs in complex and diverse cases. Indeed, complex lesions can even be challenging to detect by human operators and are therefore often underdiagnosed.[1] This is particularly the case for small aneurysms, saccular aneurysms located close to bifurcations, or rarer VAA locations such as jejunal, ileal, colic, or pancreaticoduodenal artery aneurysms. As the dataset used in this study included VAAs located mainly in the coeliac trunk branches, and a smaller proportion in the superior mesenteric artery or in the renal arteries, further studies are required to test the ability of the method in other cases.

In this dataset, the method demonstrated adequate sensitivity, but technical improvements can be achieved to further enhance the specificity. In this study, false negative detection occurred in two cases with thrombosed aneurysms. A dedicated model should be developed to detect thrombosed areas, taking advantage of the accurate segmentation of the lumen provided by the current algorithm. Adding thrombosed volume detection to the segmented lumen would improve identification of abnormal arterial dilatation in such areas. In addition, enhancing the method with additional CTAs from patients with endovascular material may help to further improve the performances of the method and generalise its use. The main issue is that VAAs represent a rare entity and it is extremely difficult in practice to obtain images in large cohorts of patients. Efforts should be directed towards developing multicentre international studies to collect imaging from these patients to facilitate development of enhanced imaging analysis to improve detection and early management of this life threatening condition.

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CONFLICTS OF INTEREST

None.

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