# Calculation of Aortic Arch Calcification Degree in Hemodialysis Patients Using Deep Learning

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*Abstract:* - Abdominal Aortic Calcification (AAC) is a common form of vascular calcification closely associated with atherosclerosis and serves as an important marker for measuring increased risk of cardiovascular, cerebrovascular, and peripheral vascular diseases. Particularly in patients with Chronic Kidney Disease (CKD) and those undergoing dialysis, the risk of AAC significantly increases due to a combination of traditional and non-traditional risk factors. Therefore, developing a rapid and accurate method to assess the extent of AAC is crucial for preventing the progression of vascular calcification and the associated risk of cardiovascular diseases. Dialysis patients are required to undergo an abdominal X-ray annually, and the degree of calcification of the abdominal aorta is assessed manually through these X-ray images. However, these methods have limitations in identifying subtle calcifications in the abdominal aorta and the assessment process is time-consuming and depends on the experience and subjective judgment of physicians. To overcome these limitations, we propose a new method that incorporates deep learning technology to improve the accuracy of assessing the extent of AAC. Our method utilizes CNN models and attention modules to enhance the model's ability to recognize features of abdominal aortic calcification.

*Key-words:* - Abdominal Aortic Calcification, Residual Network, Deep Learning, CKD, Cross-scale Attention.
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## 1. Introduction

Cardiovascular diseases are the leading cause of death among patients with chronic kidney disease (CKD) and those undergoing hemodialysis. In these patients, acute myocardial infarction, fatal arrhythmias, and heart failure are among the primary causes of cardiovascular-related mortality. Abdominal aortic calcification (AAC) is an important morphological marker of vascular pathology, reflecting the extent of vascular calcification, and is considered a significant predictor of cardiovascular events. However, the assessment of AAC scores relies on the experience and subjective judgment of physicians, leading to variability in results due to differing standards among doctors, causing confusion and requiring significant manpower. In light of this, the current paper aims to utilize artificial intelligence models to precisely measure the degree of abdominal aortic calcification in abdominal X-rays, and use this score to predict the risk of death, cardiovascular death, major cardiovascular obstruction, and peripheral vascular obstruction events in hemodialysis patients.

The main goal of this paper is to develop an artificial intelligence-based model for the accurate assessment of abdominal aortic calcification in abdominal X-rays. Additionally, this paper will explore the association between AAC scores and the risk of central vascular events and death in hemodialysis patients, aiming to establish a combined model of related risk factors and prognostic prediction models for clinical application. Developing an AAC network model that can calculate the abdominal aortic calcification score more accurately than traditional medical imaging reading has significant implications for improving the quality and clinical value of abdominal X-ray reports. By enabling early and precise assessment of abdominal aortic calcification, physicians can intervene earlier in treatment, thereby reducing the mortality rate from chronic hemodialysis, cardiovascular death, and the occurrence of major adverse cardiovascular events and peripheral vascular events. Furthermore, as a powerful predictive indicator, the abdominal aortic calcification score can help physicians better assess patient risk and devise personalized treatment plans.

## 2. Related Works

Vascular calcification (VC) is a common phenomenon of vascular aging that poses a significant threat to cardiovascular health. The abdominal aorta, one of the body's principal arteries, is responsible for transporting blood from the heart to the lower body. The presence of Abdominal Aortic Calcification (AAC) not only restricts blood flow but also reduces arterial elasticity, thereby increasing the risk of cardiovascular diseases, cerebrovascular diseases, and peripheral vascular diseases, potentially leading to death. Patients with chronic kidney disease (CKD) are particularly prone to VC, especially AAC, with a prevalence rate as high as 60% [1]. The high incidence of VC among CKD patients is partly due to traditional risk factors such as aging, hypertension, type 2 diabetes, dyslipidemia, and smoking, as well as CKD-related non-traditional risk factors, including uremia, chronic inflammation, vascular aging, and hyperphosphatemia [2].

The calcification of the abdominal aorta affects a wide range, from small to medium and large arteries. Assessing the AAC score as determined by physicians serves as an important indicator for evaluating vascular calcification and is crucial for assessing the overall vascular health. Therefore, an objective assessment of the AAC score is a significant task for clinical physicians, aiding in the early detection and formulation of treatment plans to reduce the risk of related diseases. The method of calculating the calcification score is illustrated in Fig. 2, where the abdominal aorta is divided into

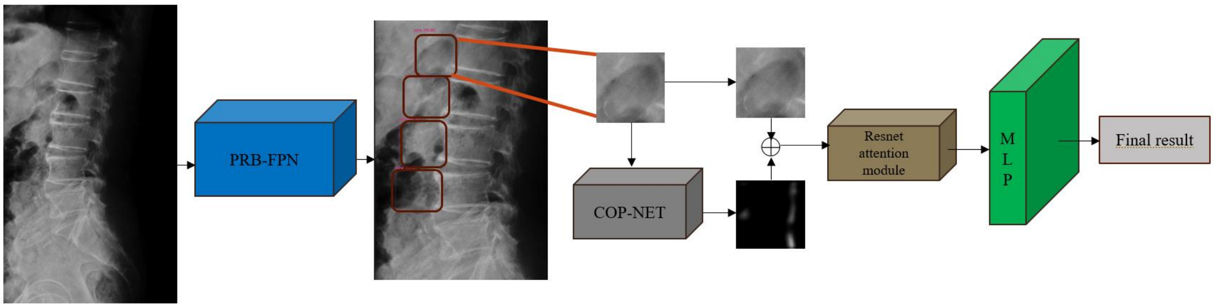


Fig. 1. The flow chart of AAC (Abdominal Aortic Calcification) Network

four sections (L1-L4) based on the position of four vertebrae, with each section further divided into the Posterior Wall(PW) and the Anterior Wall (AW), totaling eight regions.

The assessment of AAC primarily utilizes two semi-quantitative scoring systems: the Kaupplia AAC-24 point and AAC-8 point scoring scales [3,4]. The AAC-24 point scoring system rates the degree of calcification coverage on the anterior and posterior walls of the abdominal aorta across four segments in front of the L1 to L4 lumbar vertebrae, using a scoring standard of 0 to 3, with a total score ranging from 0 to 24. The AAC-8 point scoring scale, a simplified version, scores by quantifying the total length of calcification on the anterior and posterior walls in front of the L1 to L4 lumbar vertebrae, with total scores ranging from 0 to 8. Due to the convenience of AAC-8 and its sufficient clinical applicability, this paper primarily adopts AAC-8 as the accuracy classification standard, while AAC-24 is used for comparison with other research.

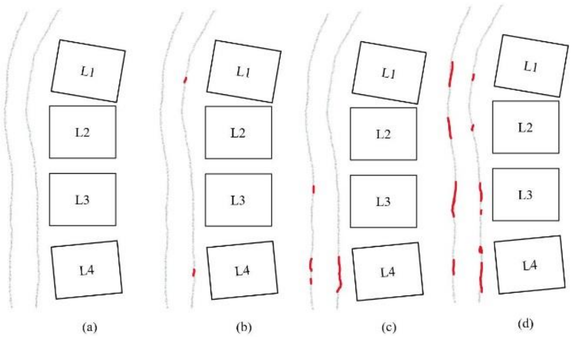


Fig. 2. Schema for AAC-24 point scale scores.*(a) 0 (b) 2 (c) 6 (d) 15* . Schema for AAC-8 point scale scores.*(a) 0 (b) 2 (c) 3 (d) 8* .

In recent years, with the rapid development and success of Convolutional Neural Networks (CNNs), many researchers have applied deep learning techniques to medical-related topics. However, the features of most medical samples are not as rich and diverse as objects in natural scenes. For example, vascular calcification in X-ray images looks very similar to normal bone, and blood vessels without calcification are completely invisible. As a result, manual inspection or traditional vision techniques may lead to misclassification. This paper proposes a new CNN architecture for automatically calculating the degree of abdominal aortic calcification in patients undergoing hemodialysis

To address the issues above, this paper introduces a network architecture called AAC-Net (Abdominal Aortic Calcification Network), which combines attention mechanisms with a CNN model. By utilizing deep learning technology for more detailed analysis of image data, this method can help physicians more accurately identify and assess the degree of abdominal aortic calcification, even at an early stage. This could contribute to early intervention, reducing the risk of cardiovascular diseases caused by vascular calcification, thereby improving patient prognosis and quality of life.

# 3. Method

The flow chart of AAC-Net is depicted in Fig. 1. This AAC network can directly analyze and detect the position of the spine from spinal X-ray images, then locate the position of the abdominal aorta. It enhances features through feature extraction and various attention modules, followed by an MLP (Multi-Layer Perceptron) network that classifies the degree of calcification in patients. The AAC network architecture is divided into detection and classification steps. Initially, our previously proposed object detector, PRB-FPN [5], is used for detecting the position of the spine. It can detect very small objects more effectively than YOLO v4 [6], through which the position of the abdominal aorta is determined. Fig. 3 shows the results of abdominal aorta detection using PRB-Net. In the classification step, a model with ResNet [7] as the backbone is used to extract features. To enhance the discriminative capability of features, we propose COP-Net (Cross-scale Overlapping Patch-based Network) to use features as an additional attention, inputting the weight map produced by COP-Net into the model. The weight map strengthens the calcification areas focused on by the classification network. Finally, classification and calculation of the calcification score are performed using a three-layer FC with ReLU. Our AAC network architecture also adopts the AAC-8 for calculating the abdominal aortic calcification score, achieving a top accuracy rate of 79.24%.

Fig. 3. Abdominal aorta detection result of PRB-FPN

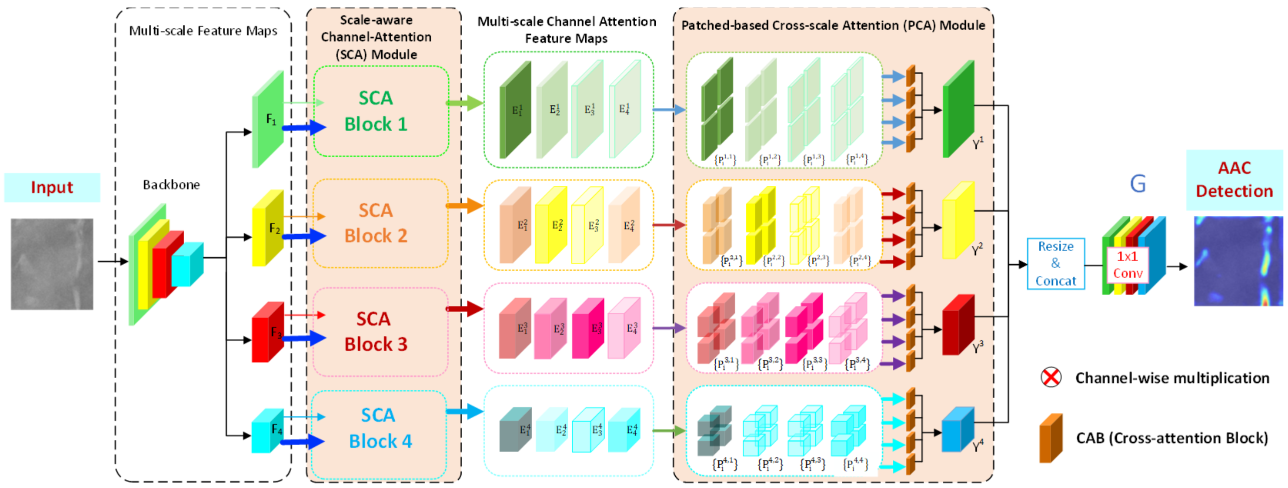


Fig. 4. Architecture of COP-Net (Cross-scale Overlapping Patch-based Network).

Fig. 4 illustrates the architecture of COP-Net, starting with the model using ResNet [7] as the backbone to obtain features. Then, through the SCA (Scale-aware Channel Attention) module, the feature maps of different channels are weighted. Next, using the PCA (Patch-based Cross-scale Attention) Module, the feature maps are divided into different patches. Through different scales of feature maps and self-attention, these feature maps undergo Query, Key, Value weighting to obtain more discriminative feature maps. Finally, AAC detection is performed using a 1x1 convolution mechanism, detecting the calcified pixel positions and generating a heatmap of the abdominal aorta AAC. The classification of abdominal aortic X-ray images and calculation of the calcification score are done using a three-layer Fully-Connected Network (or Multiple-Layer Perceptron), with the images outputting three categories representing no calcification, calcification on one side of the vessels, and calcification on both sides of the vessels.

# 4. Experiments and Results

We adopted ResNet18 [7] as the feature extraction module and experimented with various attention modules, including CBAM [8], SimAM [9], and Shuffle Attention(SA) [10], among others. These attention modules significantly enhance the discriminative ability of the backbone network for AAC classification. Fig. 5 shows our method for AAC classification, dividing a segment of the patient's spine corresponding to vascular X-ray images into three types of grading results. The results are shown in Figure 6. Table I demonstrates the performance of these three attention modules. Upon examination, we found that although both SimAM [9] and CBAM [8] aim to enhance the model's feature discriminative power, their performance in this task was slightly inferior to that of ResNet18 [7]. This result could be attributed to several factors. First, the SimAM [9]and CBAM [8] attention module may cause the model to overly focus on channel features while neglecting spatial information, which is crucial for the detection of vascular calcification. The introduction of the Shuffle Attention (SA) [10] module, which combines spatial and channel attention mechanisms, enhances feature representation by rearranging feature channels and spatial attention to facilitate cross-channel information exchange.

When calculating the calcification score for AAC, there can be individual calcifications on the posterior wall (PW) and anterior wall (AW). Without separating the inputs into PW and AW, the classifier can become confused. To further increase the accuracy of the previous classification model, we divided the input into three parts: FS (Full-Size) for the entire image, PW (Posterior Wall) portion, and AW (Anterior wall) portion. The model outputs four categories: no calcification, AW calcification, PW calcification, and calcification on both sides of the vessels. This approach has two advantages: 1. More discriminative features: Since the scoring items are composed of AW and PW, inputting them separately provides the model with additional information. 2. Finer classification: The classification task becomes four categories, which allows for the assessment of calcification in AW and PW individually (secondary tasks), thereby enhancing the accuracy of the model's classifications. Fig. 6 is the flowchart of this method, and Table II shows the accuracy of calcification score calculations for this method. Compared to Table I, there is a significant improvement in accuracy, and the highest accuracy is achieved when the SimAM [9] attention mechanism is employed.

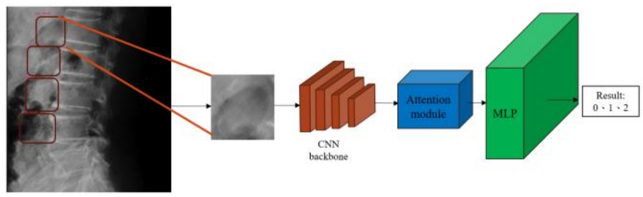


Fig. 5. Single abdominal aortic section images as input features.

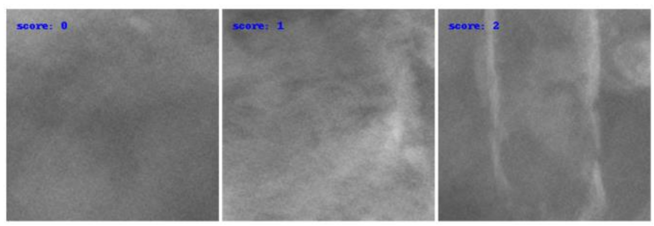


Fig. 6. Classification results of AAC score for aortic area corresponding to a single spinal segment.

Indeed, we can design a network architecture to detect the situation of abdominal aortic calcification and then use this calcification condition as a basis for feature weighting. We use a COP-Net (Cross-scale Overlapping Patch-based Network), which outputs the condition of aortic calcification into a feature heatmap. The core of COP-Net lies in its two innovative modules: the Scale-aware Channel Attention (SCA) module and the Patch-based Cross-scale Attention (PCA) module. The introduction of the SCA module enables our method to assess the importance of channels at different scales. The PCA Module slices the feature map into different patches, and then, using feature maps of different scales, employs self-attention to weight these feature maps with Query, Key, Value, obtaining more discriminative feature maps. Finally, a 1×1 convolution mechanism is used to generate a channel attention feature map that is more global and comprehensive. The heatmaps generated by COP-Net are used as weights, further input into our classification model. Using these heatmaps as weights for training the classification model means we can guide the classification model to focus on those areas that are most decisive for the final diagnosis. Fig. 8 shows the process of converting an abdominal aortic X-ray image into an arterial calcification heatmap using COP-Net; (c) shows the original image multiplied by the heatmap to obtain an enhanced feature map, and then features are extracted with ResNet and calcification scores are calculated with an MLP. The entire process is depicted in Fig. 9.

TABLE I. ACCURACY OF AAC CALCULATION WITH RESNET AND VARIOUS ATTENTION MODULES

| Model | Acc(%) |
|---|---|
| ResNet18 | 66.67 |
| ResNet18+SimAM | 64.67 |
| ResNet18+CBAM | 65.33 |
| ResNet18+SA | **69.00** |

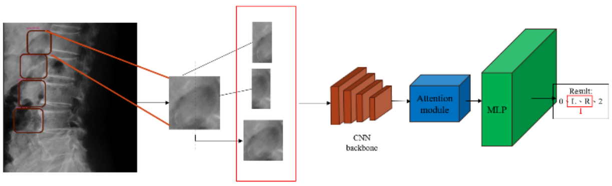


Fig. 7. Segmenting a single abdominal aortic section into three aarts as input features: full-size Image, posterior wall (PW), and anterior wall (AW).

TABLE II. ANALYSIS OF AAC SCORE CALCULATION ACCURACY USING SINGLE ABDOMINAL AORTIC SECTION SEGMENTED INTO FULL-SIZE IMAGE, ANTERIOR WALL, AND POSTERIOR WALL AS INPUT FEATURES.

| Model | Acc(%) |
|---|---|
| ResNet18 | 71.50 |
| ResNet34 | 65.00 |
| ResNet18+SimAM | **75.75** |
| ResNet18+CBAM | 74.75 |
| ResNet18+SA | 72.50 |

Table III presents an accuracy analysis of AAC score calculation using arterial calcification heatmaps as feature weighting. The second column represents the core idea of multiplying the original image by the heatmap generated by COP-Net before input, utilizing the heatmap to highlight key feature areas. These areas' information is directly integrated into the original image in an attentional manner, thereby enhancing the model's accuracy in calculating AAC scores. By multiplying the heatmap with the original image, we effectively focus the model's attention on key abnormal areas such as abdominal aortic calcification. This method not only preserves the detailed information in the original image but also enhances the model's ability to recognize markers of specific health conditions. The third column represents the accuracy of AAC score calculation by the network when the original image and the heatmap generated by COP-Net are concatenated. The results show that concatenation can more precisely identify the presence and extent of abdominal aortic calcification, thus achieving higher classification accuracy.

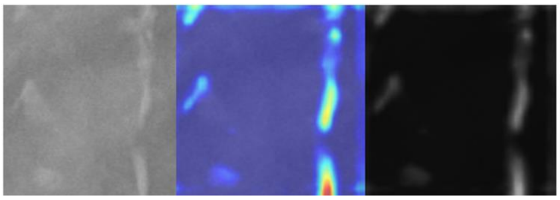

Fig. 8. Transforming (a) into a heatmap of arterial calcification using COP-Net as shown in (b); (c) the original image multiplied by the heatmap to obtain an enhanced feature map.

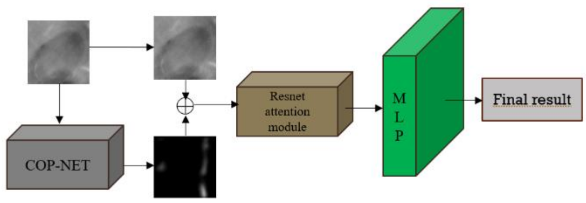


Fig. 9. Using COP-Net to transform abdominal aortic images into heatmaps of arterial calcification, followed by multiplying the original images by the heatmap to obtain enhanced feature maps. Then, features are extracted using ResNet and calcification scores are calculated with MLP.

TABLE III. ANALYSIS OF ACCURACY IN AAC SCORE CALCULATION USING ARTERIAL CALCIFICATION HEATMAPS AS FEATURE WEIGHTING.

| Model | Input | | |
|---|---|---|---|
| | *Original Acc(%)* | *Weighting Acc(%)* | *Concatenation Acc(%)* |
| Resnet18 | 66.67 | 72.46 | 75.00 |
| Resnet18+SimAM | 64.67 | 76.27 | 77.56 |
| Resnet18+CBAM | 65.33 | 76.69 | 79.24 |
| Resnet18+SA | 69.00 | 77.12 | 78.73 |

Furthermore, we compared and adjusted our model's output to calculate AAC scores in the AAC-24 point, adopting the same classification standards as [11], categorizing each patient into low, medium, and high levels according to their AAC scores. Table IV shows the accuracy analysis of AAC score calculation using the same scoring method as [11]. Our method achieved an accuracy of 86.66%, surpassing the average accuracy rate of 80.08% reported in [11]. The grading formula used in the paper, where $Z_i$ represents the patient's AAC score, is as follows:

$$F(Z_i) = \begin{matrix} 0(low) & Z_i < 2, \\ 1(modrate) & 2 \le Z_i < 6, \\ 2(high) & Z_i \ge 6. \end{matrix}$$

TABLE IV. ANALYSIS OF ACC SCORE CALCULATION ACCURACY USING THE SAME SCORING METHOD AS DESCRIBED IN [11].

| Method | Acc(%) |
|---|---|
| [11] | 80.08 |
| our method | 86.66 |

# 5. Conclusion

The AAC grade is an essential indicator of vascular calcification (VC) and is closely linked to vascular diseases. We have developed a CNN-based attention model for classifying AAC grades, incorporating various attention blocks to amplify subtle features. Compared to conventional feature extraction backbone networks, our method achieves precise classification of AAC grades. We believe this model can aid physicians in reducing the time needed for interpretation and enhancing the accuracy of their assessments, thereby enabling more objective treatment planning.

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**Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)**

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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**Conflict of Interest**

The authors have no conflicts of interest to declare that are relevant to the content of this article.