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Coronary Calcium Detection Based on Improved Deep Residual Network in Mimics

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Abstract
Coronary calcium detection in medicine image processing is a hot research topic. According to the low resolution and complex background in medicine image, an improved coronary calcium detection algorithm based on the Single Shot MultiBox Detector (SSD) in Mimics is proposed in this paper. The algorithm firstly uses the aggregate channel feature model to preprocess the image to obtain the suspected calcium area, which greatly reduces the time of single-frame image detection. The basic network VGG-16 is replaced by Resnet-50, which introduces the identity mapping to solve the problem of reducing the detection accuracy when the number of network layers are increased. Finally, the powerful and flexible two-parameter loss function is used to optimize the training deep network and improve the network model generalization ability. Qualitative and quantitative experiments show that the performance of the proposed detection algorithm exceeds the existing calcium detection algorithms, and the detection efficiency is improved while ensuring the accuracy of calcium detection.

Keywords Coronary calcium detection · Single Shot MultiBox Detector · Identity mapping · Loss function · Resnet network · Suspected calcium area · Aggregate channel feature

Introduction

Coronary artery disease (CAD), also known as ischemic heart disease (IHD), is the most common of the cardiovascular diseases [1]. Types include stable angina, unstable angina, myocardial infarction, and sudden cardiac death. Coronary atherosclerotic heart disease is a heart disease called coronary heart disease [2], which results from coronary atherosclerotic lesion causing stenosis and blockage of vascular lumen and myocardial ischemia, hypoxia, or necrosis. The clinical manifestations of coronary heart disease are usually chest pain or discomfort, heartburn and dyspnea, myocardial infarction and sudden death. The traditional clinical diagnosis mainly depends on the ways, which are electrocardiogram (ECG) [3], electrocardiogram stress detection, ventilation perfusion imaging [4], ultrasonic cardiogram, angiography and coronary artery CT. However, the sensibility and specificity of those diagnostic methods are not perfectly high, and electrocardiogram changes caused by myocardial hypertrophy and myocarditis can easily cause diagnostic error. Only when coronary artery stenosis is greater than 75% can cause discomfort and electrocardiogram changes [5].

At present, many researchers have done a lot of research on coronary calcium detection and recognition. CT is the commonly method used to detect coronary artery stenosis. The object area is selected first and calculated geometric center as seed point in literature [6], where the extracted coronary artery edge is mapped to the next frame image, and the mapped pixel is selected as the seed point of this frame; the coronary artery is semi-automatic extracted by region growth algorithm; local cube extraction detection algorithm based on region growth algorithm is introduced by Araki T et al. so as to realize blood vessel extraction of coronary arterial tree [7]; A novel algorithm based on probabilistic decision is proposed by Chaikriangkrai K et al. which is to extract bigger coronary artery [8]. However, due to the limitation of CT image, it has low resolution (about 0.5 mm) [9], where it can only estimate

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the position and degree of coronary artery stenosis. In addition, these artifacts manifest in typical patterns containing intensity undershoots and arcshaped blurring due to the CT reconstruction geometry (see Fig. 1) and potentially limit or even preclude the evaluation of parts of coronary calcium in coronary arteries or cause misinterpretations [10–14].

With the breakthrough in object recognition and medical diagnosis areas, researchers from home and abroad extend the deep learning model and apply it to the coronary calcium detection, which are obtained from deep learning algorithm represented by convolutional neural networks [15]. In deep learning algorithm, feature extraction network layer is the core technology of the whole framework, whose functions are equal to histogram of oriented gradient and DPM. However, the only somewhere different is that the feature extracted by CNN is not manual design but learning by means of training networks, so that CNN can extract more crucial features and get greater effect. Classification network layer is equal to SVM, by learning and using the information extracted by the former network to classify whether it is a coronary calcium in images. The coronary calcium detection algorithm based on deep learning can be divided into two types: area selection, which is also called extraction of candidate box, such as R-CNN, SPP-Net, Faster-RCNN, R-FCN [16–18]; the recursion networks based on end-to-end, such as YOLO, SSD [17]. The object detection is transformed to classification and regression problems by the former, adopting independent area to extract network and calculate the suspected area, using bounding box to amend the location of the extracted area and classifying by softmax; the object detection is taken as a regression problem by the latter, processing the image by deep networks, obtaining locations of the whole objects in the image, their categories and corresponding confidence probability. It can be seen that the latter integrates the detection process into a regression problem, which makes network structure easy and detection speed faster; meanwhile, since the network has no branches, the training process can only be completed once [19]. Thus, the object detection model transformed to regression problem is perfectly effective. Although the coronary calcium detection algorithm based on deep learning is quickly developed, there is also an improved space in the aspect of accuracy and speed. The goal of our proposed algorithm is to reduce cost under the condition of keeping detection accuracy.

Combining with many years of experience in medical image processing algorithm and through the analysis of traditional model and deep network, a deep network coronary calcium detection algorithm based on improved SSD model is proposed. The image is preprocessed by the aggregate channel feature model, and then the suspected object area is obtained, which greatly reduces the time of detecting single frame image; replace VGG-16 with Resnet-50 for the basic network of SSD, and solve the problems that network layer depth and detection accuracy decline by increasing identity mapping; finally, a strong and flexible two-parameter loss function is adopted to optimize the training deep network and improve generalization abilities of network model.

Related works

SSD deep model

The core of SSD model is to obtain object categories and corresponding location deviation in many given bounding boxes by using convolution filtering in feature image. Comparing with YOLO model, SSD model replaces convolutional layer with the whole connection layer of YOLO, realizing multi-scale object location prediction, and its process framework is shown in Fig. 2. SSD model is mainly improved based on VGG16 network, and replaces the whole connection layer with convolutional layer. Meanwhile, it also adds maximum pooling

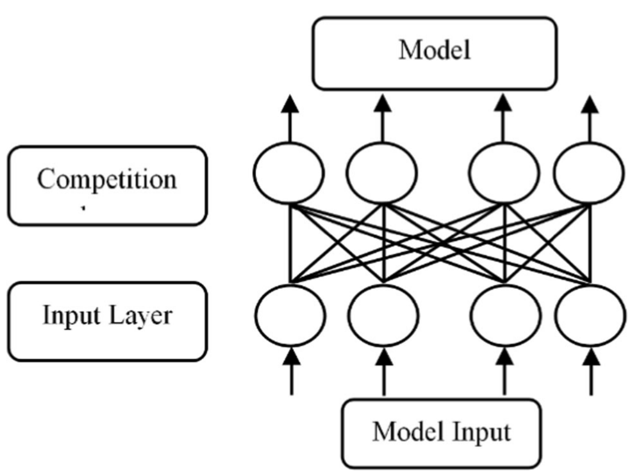

Fig. 1 Difference of coronary calcium under different imaging conditions with motion, blur; (a)Artifacts effect; (b) Motion blur

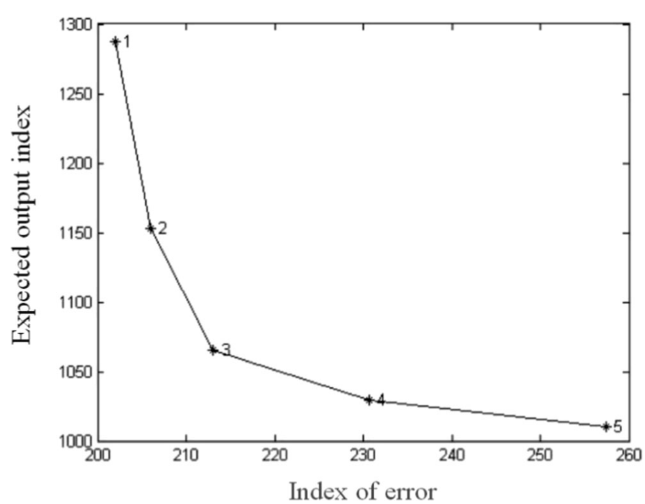

Fig. 2 Detection framework of SSD model

Layer in network and outputs a corresponding feature image for convolutional layer as predicted output. In other words, those multi-scale feature images can be used as predicted output and then to obtained multi-scale result. In order to realize multi-layer mapping, the 3×3 size, rather than 5×5, 7×7, 11×11 size adopted by VGG16 network [20], of convolution kernels are adopted to describe features. So low- and high-level deep features in imaging sequences can be extracted at the same time.

The obtained each location in feature image correspond to a series of fixed size of frames under different scales, where each grid has k rectangle boxes and each rectangle box can predict c object categories and their corresponding location error. If the obtained size of feature image is $m \times n$, $m \times n$ feature grids can be obtained and $(c+4) \times k \times m \times n$ outputs can be haven. In the stage of training, if rectangle box matches to template box successfully, the rectangle box is positive sample; on the contrary, it is negative sample [21]. Only positive sample of SSD model can participate in the calculation of the cost function, and learn the location information of the detection box with high confidence degree first and then learn the information of categories. So in the stage of training, the obtained number of positive samples is less, which make network training has lower cost finally.

The objective cost loss function of SSD model results from weight of position loss term and confidence loss term, and its formula is described as follows:

$$L(x,c,l,g) = \left(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)\right)/N \tag{1}$$

where c represents confidence of multi-category object attributes; l and g represent the obtained predictive box and template box respectively; N is the matching number of rectangle box; α is the regularized weight coefficients for cross validation.position loss term $L_{loc}(x, l, g)$ is obtained by regularized term $\mathrm{smooth}_{\mathrm{L1}}$ between l and g. By processing deviation regression on the multi-scale rectangle box of different location centers, the optimized matching point location is obtained and its formula is listed as follows:

$$L_{loc}(x,l,g) = \sum_i \sum_m x_{ij}^k smooth_{\mathrm{L1}}\left(L_i^m - \hat{g}_j^m\right) \tag{2}$$

where x_{ij}^k represents the matching results between the$i$th rectangle box and the jth reference box in class attribute$k$. If $x_{ij}^k = 1$, it represents that the results are consistent; on the contrary, they are inconsistent. Confidence degree loss term $L_{conf}(x, c)$ is obtained by calculating Softmax loss function of multi-category attributes, which formula is as follows:

$$L_{conf}(x,c) = -\sum_{i \in pos} x_{ij}^p \log\left(\hat{c}_i^p\right) - \sum_{i \in neg} \log\left(\hat{c}_i^0\right) \tag{3}$$

The convolutional layer is added to SSD model and the feature set is obtained, which are help to realize multi-scale object detection. Different levels of networks can capture different levels of features in medicine image, and the experimental result has shown that more detailed are obtained and the semantic representation ability of the target is increased by low-level features [22].

Deep residual network

Introducing residual blocks is the key core point of Deep Residual Network (ResNet), which processes residual learning on the identity mapping layer superimposed by a shallow network, and improves the accuracy extracted by deep features. So the problem of vanishing gradient is solved. Supposing the original input sample of ResNet is x, and $F(x)$ can be obtained after multi-layer network mapping, thus, residual function $H(c) = F(x)\text{-}x$ is shown as Fig. 1. It can be seen that after an identity mapping, superimposing output to convolutional output, forming a jumping connection that can jump a layer or a lot of layers and eliminating vanishing gradient, can make deep networks become hundreds of layers, Fig. 3 shows schematic diagram of the sub-block construction of Resnet.

Identity mapping is easily superimposed in the networks, though increase the number of layers but reduce network performance. The structure of Fig. 1 is easily able to make the weight of multiple nonlinear layers approach zero to approximate the identity mapping, and its output can be shown as:

$$y = H(x, W_i) + x \tag{4}$$

where x and y represent the input and output results of sub-blocks respectively, and $H(x, W_i)$ is convolutional mapping. The introduced x neither introduce extra parameter nor increase the computational complexity. The simulation experiment results indicates that comparing with the same simple networks, Resnet network is not affected by the deep of the network, is easier to be converged and greater output results.

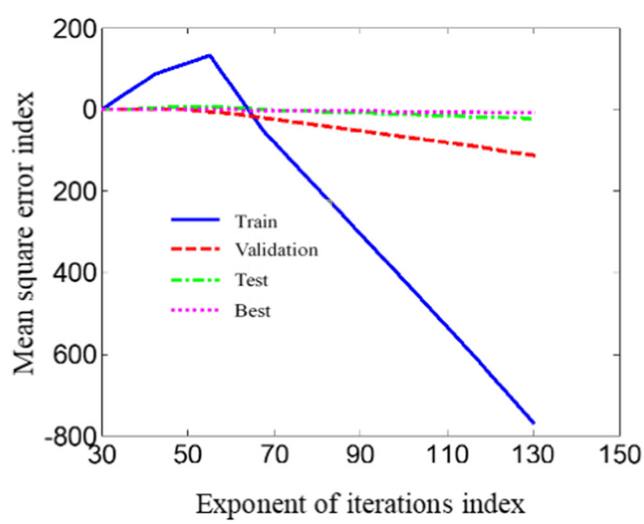

Fig. 3 Schematic diagram of the sub-block construction of Resnet

The improved deep calcium detection network

The existing deep network object detection algorithm emphasizes on high-level features of the extracted image including global features and ignores low-level features. Rich local details, which can obtain satisfactory human visual effect and have substantial effect on the coronary calcium detection, are included in low-level features; high-level features are mainly concerned on a wide receptive field to ensure the super-resolution reconstruction of image accuracy. Based on SSD model, an improved coronary calcium detection algorithm is proposed in this paper. The algorithm preprocesses image by using aggregate channel feature model and the suspected object area is obtained, which greatly reduce the detection time of a single frame image; then the basic network VGG-16 of SSD is replaced with Resnet-50, and the problem of deepening network layers but decreasing detection accuracy is solved by increase identity mapping; finally, strong and flexible two-parameter loss function is adopted to optimize the training deep networks and improve the generalization ability of network model.

The quick detection based on ACF

The sliding window is commonly adopted by the coronary calcium detection algorithm to process exhaustive search. By taking some strategies, candidate window is formed, and classify the candidate areas by using classification algorithm. However, due to the large difference in the shape of the coronary calcium, the complexity of screening candidate windows by multi-scale is too large, and classification is very inefficient. In order to improve the efficiency of the detection, the object detection algorithm based on ACF model is used to preprocess the image firstly in this paper and then form the candidate window. Experimental simulation shows that the candidate area window almost includes all the possible object areas in the image, which greatly reduces the number of the suspected targets and basically has a low undetected detection effect on any coronary calcium in the image.

Supposing the detected image has M suspected areas, which can be shown as $\left\{\mathrm{B}^i \in R^{m_i \times n_i} | i = 1, 2, \ldots, M\right\}$. Because the input parameters of Resnet and classifier must be the same, all candidate areas must be normalized to a uniform scale $\{\mathrm{D}^i \in R^{m \times n} | i = 1, 2, \ldots, M\}$.

The improved SSD model based on Resnet

As we all know, Resnet solves the problems of deepening network layer and reducing the detection accuracy. Because Resnet has less filters and lower computational complexity comparing with traditional VGG, the benchmark network of SSD is changed by replacing VGG with Resnet-50. The multi-level feature extraction adopted by SSD model leads to the obtained feature information redundant, which directly affects the training complexity, and has a curse of dimensionality problem. Thus, processing feature extraction on input data by pre-network and providing output information for subsequent network layer can increase subsequent training speed and improve the generalization of the network.

The structure of Resnet-50 adopts multiple residual structures with different levels, where different number of residual units are included in each convolutional block and each unit can process three times convolutional performance. Because convolutional structure has multiple identity mappings, it cannot reduce the performance of network when the network layers are increased. In Eq. 4, identity mapping $H(x, W_i)$ is written as $W_2\sigma(W_1x)$, where σ is activation function Relu. If the input and output dimension of the convolutional block is not same, it's essential to process projection transformation on input x, and eliminate the differences among dimensions, so its formula is shown as follows:

$$y = H(x, W_i) + x \tag{5}$$

In the coronary calcium detection for Mimics environment, its data processing equipment has a low power requirement. So the clipped convolutional structure Resnet-50 is adopted to process network replacement, where the obtained object area is processed feature extraction by the second layer of network and is described respectively by convolution kernels of $1 \times 1 \times 16$, $3 \times 3 \times 64$, $1 \times 1 \times 256$; the convolution kernels of $1 \times 1 \times 128$, $3 \times 3 \times 128$, $1 \times 1 \times 512$ are respectively used for the third layer of convolutional network; the convolution kernels of $1 \times 1 \times 256$, $3 \times 3 \times 256$, $1 \times 1 \times 1024$ are respectively used for the fourth layer of convolutional network; the convolution kernels of $1 \times 1 \times 512$, $3 \times 3 \times 512$, $1 \times 1 \times 2048$ are respectively used for the fifth layer of convolutional network; the remaining network structure is consistent with VGG16. Preprocessing the target by adopting feature image with different sizes can accurately detection the multi-scale target. The improved model proposed by this paper not only is the detection network of end-to-end, but also can process parameters sharing and transferring, which strengthens the efficiency of feature extraction. In the obtained multi-scale feature mapping image, the output results of different feature locations correspond with the areas to be detected in the output image [23]. Because there has differences between multi-scale feature image and detection box, the adaptive rectangular box extraction strategy is adopted. Supposing there are m targets in feature mapping image and their corresponding sizes can be shown as:

$$s_i = s_{\min} + \frac{s_{\max} - s_{\min}}{m-1}(i-1) \tag{6}$$

Where $i \in [1, m]$, $s_{\min}$, $s_{\max}$ respectively represent the minimum and maximum scale of the rectangular boxes in deep results. The length-width ratio $r \in \{1, 2, 3, 1/2, 1/3\}$ of the formed rectangular box is an optimum search strategy and its corresponding length and width are respectively $w_i^\alpha = s_i \sqrt{r}$ and $h_i^\alpha = s_i \sqrt{r}$. Selecting rectangular boxes through the above strategy can strengthens the coverage accuracy of the final coronary calcium and enhance the computing efficiency of the subsequent cost loss function [24].

Dual-parameter loss function

A generalized two-parameter loss function, which can spread to many popular robust loss functions, is proposed in this paper. Supposing the error is e before and after iteration, so the adopted loss function in this paper can be shown as:

$$L(e, \alpha, \beta) = \begin{cases} \log\left(0.5\left(\frac{e}{\beta}\right)^2 + 1\right) & \alpha = 0 \\ 1 - \exp\left(1 - 0.5\left(\frac{e}{\beta}\right)^2\right) & \alpha = -\infty \\ \frac{\rho(\alpha)}{\alpha}\left(\left(\frac{1}{\rho(\alpha)}\left(\frac{e}{\beta}\right)^2 + 1\right)^{\frac{\alpha}{2}} - 1\right) & \textit{otherwise} \end{cases} \tag{7}$$

where $\rho(\alpha) = \max(1, 2 - \alpha)$; α, β are parameters with continuous value attribute, which can simulate any loss functions through different parameter setting, such as mean square error loss function(l_2), absolute error loss function(l_1) and so on [25]. Comparing with traditional fixed parameter loss function, by adjusting α and β slightly, the two-parameter loss function adopted by this paper can obtain better loss functions, which have great flexibility and apply in more complex medicine image.

Experimental results and analysis

Data sets and parameter setting of the experiment

To evaluate the performance of the improved deep network for coronary calcium detection, the training setsare collected by the department of medical imaging, and have 23,589 positive samples and 23,991 negative samples. And the test sets select the internationally widely used and very challenging public detection database with a total of 820 images.

The deep network is structured by convolutional structure model Resnet-50 in this paper. In the stage of training, the minimum batch setting is 16; when adopt gradient descent algorithm to optimize in weight update rules, the initial value of learning rate is set as 0.25 and change the rate of learning to 0.025 after arriving to the thirtieth Epoch (Epoch refers to a round of traversal of all training data); if after one hundred Epoch, the proposed loss function has not changed, stop the training. To improve the efficiency of optimizing, ADAM optimization algorithm [26] is used by this paper, which is the expanded form of the random gradient descent algorithm and can iteratively update the weight of the neural network based on training data. The parameters are set as: alpha = 0.001, beta1 = 0.9, beta2 = 0.999 and epsilon = 10.8. The minimum and maximum scale of rectangular box are set as $s_{\min} = 0.15$ and $s_{\max} = 0.95$. In the loss function, α and β are respectively set as 1.12 and 0.05.

Comparison algorithms and evaluation indexes

To verify the effectiveness of the coronary calcium detection algorithm and combine with the characteristics of the proposed algorithm in this paper, the selected compare algorithms are ConvNet [18], YOLO-v2 [23], SSD [19], R-CNN [26]. The detection error tradeoff (DET) curve is selected to evaluate the detection effect of coronary calcium, where DET characterize the relation between detection rate and FPPI. The experimental environment is: Intel Xeon CPU ES 1620 V33.5GHz, 16GB, Nvidia Geforce GTX 1080, Ubuntul6.04 and 64-bit operating system. In addition, Materialise Mimicsis adopted for medical image processing, which can calculate surface medicine image models from stacked image data such as Computed Tomography (CT), Micro CT, Magnetic Resonance Imaging (MRI), Confocal Microscopy, X-ray and Ultrasound, through image segmentation. The ROI, selected in the segmentation process is converted to a calcium surface model using an adapted marching cubes algorithm that takes the partial volume effect into account, leading to very accurate coronary calcium models, where the files are represented in the STL format.

Qualitative and quantitative comparison of coronary calcium detection

To quantitatively analyze the coronary calcium detection performance in different comparison algorithms, Fig. 4 shows the relationship curve between the detection rate of coronary calcium and FPPI of the comparison algorithm, where FPPI indicates the average amount of coronary calcium can be detected in each image [27].

It can be seen from the data that the detection algorithm proposed by this paper has a higher detection rate than ConvNet algorithm, YOLO-v2 [26], SSD algorithm, R-CNN algorithm. And especially aiming at the dim-small calcium in medicine data-set, it has greatly detection accuracy and efficiency. Because FPPI is statistical result under different detection rate, in order to compare the practical detection condition of deep network, this paper mainly discusses the detection results of each algorithms when FPPI = 1 to directly analyze them. In left-heart CT image, when FPPI = 1, the detection

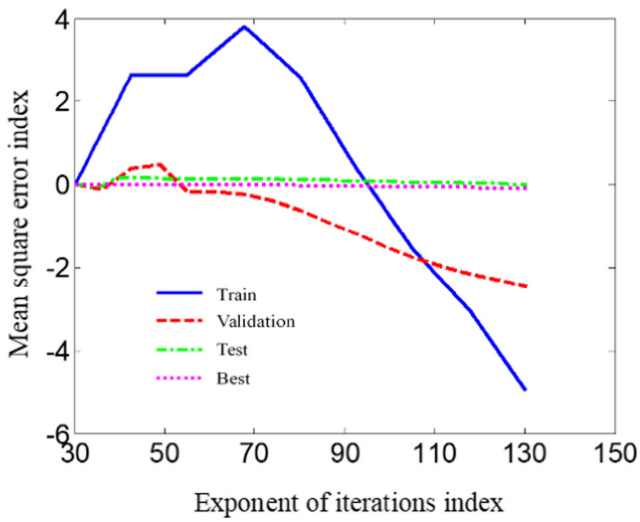

Fig. 4 The relationship curve between the detection rate of coronary calcium and FPPI for different algorithms

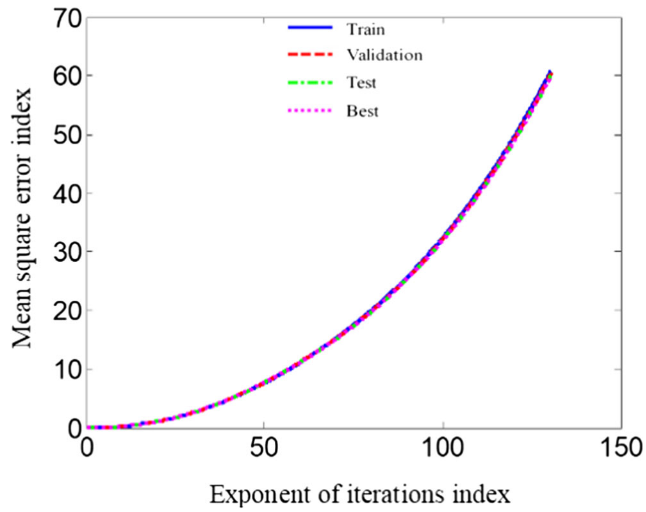

Fig. 5 The coronary calcium zone detected by the deep model proposed in this paper, where this is the sub-patch area detect in the CT images, and each calcium area is enlarged for observation

rate of our proposed paper is 77.21% while YOLO-v2 algorithm in comparison algorithm has the best result that is 75.44%. However the detection rate of ConvNet algorithm is 69.1%; the detection rate of SSD algorithm is 71.88%; the detection rate of R-CNN algorithm is only 67.1%. The reason is that most coronary calcium detection algorithms of deep feature only use multi-level deep information directly but ignore the problem of vanishing gradient. However, the improved SSD network is replacing VGG-16 with Resnet-50, solving the problem of deepening network layer and reducing detection accuracy by adding identity mappings. In addition, strong and flexible two-parameter loss function is introduced to optimize and train deep network, which improves the generalization ability of network model. Thus, deep convolutional network based on coronary calcium imaging characteristics can be greatly extracted by the proposed deep network. And strengthening training through the improved predictable rectangular box can further decrease the error rate of each medicine image. Table 1 shows detection rate of coronary calcium.

Figure 5 shows a more representative detection result, where the medicine image is ambiguous, resulting in poor visual quality. This seriously affects the detection of the coronary calcium, which is in line with the real CT imaging environment. Because there are many comparison algorithms selected in this paper, all of them are inconvenient for readers to read in one image. Figure 5 The coronary calcium zone detected by the deep model proposed in this paper, where this is the sub-patch area detect in the CT images, and each calcium area is enlarged for observation. Therefore, due to space limitations, this paper only labels and compares representative algorithms. It can be seen that the deep residual SSD training model proposed in this paper can accurately detect the coronary calcium region in complex background, especially for the fuzzy coronary calcium target, and the direct SSD model has some weak small calcium calcium. The missed detection is mainly due to the characterization ability of the deep residual SSD. However, if the image contains a large amount of coronary calcium, the model in this paper cannot completely label all the coronary calcium regions. On the one hand, the complex environment makes the coronary structure very different, and it is difficult to distinguish the area where the coronary calcium is located without reasoning. It can also be said that the algorithm of this paper still has some areas for improvement. However, according to the results of the comparison algorithm, our proposed algorithm has higher accuracy in the performance of coronary calcium detection.

Table 1 Detection rate of coronary calcium (FPPI = 1)

Algorithms	YOLO-v2	ConvNet	SSD	RCNN	Proposed
Detection rate	75.44%	69.1%	71.88%	67.1%	77.21%

Conclusions

Coronary calcium detection in medicine image processing is a hot research topic. According to the low resolution and complex background in medicine image, this paper was based on the Single Shot MultiBox Detector (SSD), proposed an improved coronary calcium detection algorithm. The algorithm firstly uses the aggregate channel feature model to preprocess the image to obtain the suspected calcium area, which greatly reduces the time of single-frame image detection. The basic network VGG-16 is replaced by Resnet-50, which introduces the identity mapping to solve the problem of reducing the detection accuracy when the number of network layers are increased. Finally, the powerful and flexible two-parameter loss function is used to optimize the training deep network and improve the network model generalization ability. Qualitative and quantitative experiments show that the performance of the proposed detection algorithm exceeds the existing calcium detection algorithm, and the detection efficiency is improved while ensuring the accuracy of calcium detection. We investigated how deep network contributes to the overall detection result, especially where heartbeat most affects the targeted Coronary calcium detection. Data-sets from different slices are used to train and test our algorithm. The overall classification accuracy reaches 77.1%. The work of this paper can greatly reduce the time spent by doctors in identifying plaques, reduce the subjectivity and diversity among different doctors, and assist clinicians in the diagnosis and treatment of coronary heart disease.

Compliance with ethical standards

Conflict of interest We declare that we have no conflict of interest.

This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent was obtained from all individual participants included in the study.

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