

METHOD AND DEVICE FOR DETECTING AND POSITIONING MEDICAL IMAGE LESION, EQUIPMENT AND STORAGE MEDIUM

FIELD OF INVENTION

[0001] The application relates to the field of deep learning technology, and in particular to a method and a device for detecting and positioning a medical image lesion, an equipment, and a storage media. .

BACKGROUND OF INVENTION

[0002] Using artificial intelligence algorithms to classify, identify, detect and locate different lesion signs in medical images can provide qualitative imaging indicators for clinical diagnosis. Conventional deep learning classification methods can recognize different types of lesions but cannot provide location information of suspected lesions. For the conventional deep learning target detection methods, during model training, the lesion area in the sample image needs to be manually marked with accurate border information, and the number of sample images are often extremely large, usually more than 10,000, which leads to a huge amount of labeling work, and it is difficult to achieve rapid model update and learning.

[0003] Therefore, finding a method that has a small amount of labeling work and can realize the detection and positioning of medical image lesions has become an urgent problem for those skilled in the art.

SUMMARY OF THE INVENTION

[0004] The embodiments of the present application provide a method and a device for detecting and positioning a medical image lesion, a computer equipment, and a storage media, so as to solve the problem of huge labeling workload of existing detection methods.

[0005] A method for detecting and positioning a medical image lesion, comprises the steps of:

[0006] obtaining a target medical image of a lesion to be detected;

[0007] inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image;

[0008] extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;

[0009] extracting a weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model;

[0010] for each of the preset lesion types, calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types;

[0011] resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;

[0012] determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and

[0013] adding the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

[0014] A device for detecting and positioning a medical image lesion, comprises:

[0015] a medical image obtaining module, for obtaining a target medical image of a lesion to be detected;

[0016] an image input module, for inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model,

wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents the probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image;

[0017] a first feature map extraction module, for extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;

[0018] a weight value extraction module, for extracting a weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model;

[0019] a fusion feature map calculation module, for calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types, for each of the preset lesion types;

[0020] a generic activation map generation module, for resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;

[0021] a connected area determination module, for determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and

[0022] a marked border adding module, for adding the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

[0023] A computer equipment, comprising a memory, a processor, and computer readable instructions stored in the memory and run in the processor, wherein the steps of the above-mentioned method for detecting and positioning a medical image lesion are

implemented when the processor executes the computer readable instructions

[0024] One or more computer readable storage stored with computer readable instructions, the computer readable storage medium stores computer readable instructions so that the one or more processors execute the steps of the above-mentioned method for detecting and positioning a medical image lesion.

[0025] The details of one or more embodiments of the present application are presented in the following drawings and descriptions, and other features and advantages of the present application will become apparent from the description, drawings and claims.

BRIEF DESCRIPTION OF THE DRAWINGS

[0026] In order to explain the technical solutions of the embodiments of the present application more clearly. The drawings that need to be used in the description of the embodiments of the present application are briefly introduced as follows. Obviously, the drawings in the following description are only some of the embodiments of the present application. For those of ordinary skill in the art, other drawings can be obtained based on these drawings without creative labor.

[0027] FIG. 1 is a schematic diagram of an application environment of the method for detecting and positioning a medical image lesion in accordance with an embodiment of the present application;

[0028] FIG. 2 is a flowchart of the method for detecting and positioning a medical image lesion in accordance with an embodiment of the present application;

[0029] FIG. 3 is a schematic flowchart of training a deep learning model in an application scenario of the method for detecting and positioning a medical image lesion in accordance with an embodiment of the present application;

[0030] FIG. 4 is a schematic diagram of the network structure of a deep learning model in accordance with an embodiment of the present application;

[0031] FIG. 5 is a schematic flowchart of step 107 of the method for detecting and positioning a medical image lesion in an application scenario in accordance with an

embodiment of the present application;

[0032] FIG. 6 is a schematic flowchart of distinguishing positive/negative lesions in an application scenario of the method for detecting and positioning a medical image lesion in accordance with an embodiment of the present application;

[0033] FIG. 7 is a schematic flowchart of determining a preset confidence threshold in an application scenario of the method for detecting and positioning a medical image lesion in accordance with an embodiment of the present application;

[0034] FIG. 8 is a schematic structural diagram of a device for detecting and positioning a medical image lesion in an application scenario in accordance with an embodiment of the present application;

[0035] FIG. 9 is a schematic structural diagram of a device for detecting and positioning a medical image lesion in another application scenario in accordance with an embodiment of the present application;

[0036] FIG. 10 is a schematic structural diagram of a connected area determination module in accordance with an embodiment of the present application; and

[0037] FIG. 11 is a schematic diagram of a computer equipment in accordance with an embodiment of the present application.

DESCRIPTION OF THE EMBODIMENTS

[0038] The following will clearly and completely describe the technical solutions in the embodiments of the present application in conjunction with the accompanying drawings in the embodiments of the present application. Obviously, the described embodiments are part of the embodiments of the present application, rather than all of them. Based on the embodiments in the present application, all other embodiments obtained by a person of ordinary skill in the art without creative work shall fall within the protection scope of the present application.

[0039] The method for detecting and positioning a medical image lesion, provided in the

present application, can be applied in the application environment as shown in FIG. 1, wherein the client communicates with the server through the network. wherein, the client can be, but not limited to, various personal computers, notebook computers, smart phones, tablet computers, and portable wearable devices. The server can be implemented as an independent server or a server cluster composed of multiple servers.

[0040] In an embodiment, as shown in FIG. 2, a method for detecting and positioning a medical image lesion is provided. Taking the method applied to the server in FIG. 1 as an example, the method includes the following steps:

[0041] 101. Obtain a target medical image of a lesion to be detected.

[0042] In this embodiment, first, the server may obtain a target medical image of a lesion to be detected, and the target medical image may specifically be an OCT (Optical Coherence tomography) image, a CT (Computerized tomography) image, and so on.

[0043] It should be noted that the target medical image must have the same image type as the medical image sample used in the training of the subsequent deep learning model. Or, in the subsequent step 102, a deep learning model with the same image type as the training sample and the target medical image is selected for recognition.

[0044] 102. Input the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, and each element in the target sequence is a first confidence corresponding to each of the preset lesion types. The first confidence represents the probability that the target medical image belongs to the corresponding preset lesion type, and the deep learning model is obtained by pre-training the medical image samples corresponding to the each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image.

[0045] After obtaining the target medical image, the server may input the target medical image into a pre-trained deep learning model to obtain the target sequence output by the deep learning model. Each element in the target sequence corresponds to each of the preset

lesion types through a fixed position. For example, suppose a total of the preset lesion types is 4, which are "Pigment epithelial detachment", "Intraretinal effusion", "Drusen" and "Macular epiretinal membrane", and assuming the target sequence is "0.8, 0.3, 0.2, 0.1". It means that the probability of "Pigment epithelial detachment" being positive is 0.8, and the probability of "Intraretinal effusion" being positive is 0.3, the probability of "Drusen" being positive is 0.2, and the probability of "Macular epiretinal membrane" being positive is 0.1.

[0046] It should be noted that the target sequence is an intermediate concept, which is mainly used to elicit the above-mentioned first confidence and the relationship between the first confidence and the preset lesion type. For the deep learning model in this embodiment, it is required that the output is the probability corresponding to the lesion type, so that the maximum connected area determined from the category activation image, which is transformed from the fusion feature map in the subsequent steps, can be guaranteed to be the location of the lesion to be detected, that is, the place wherein the solution needs to be located.

[0047] To facilitate understanding, the pre-training process of the deep learning model will be described in detail below. Further, as shown in FIG. 3, the deep learning model is obtained by pre-training through the following steps:

[0048] 201. Obtain multiple medical image samples for training.

[0049] 202. For each of the medical image samples, mark a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical image samples. Each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0.

[0050] 203. For each of the labeled medical image samples, input each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence

output by the deep learning model and corresponding to each of the medical image samples, each element in the sample sequence is a second confidence corresponding to each of the preset lesion types, and the second confidence represents the probability that each of the medical image samples belongs to a corresponding preset lesion type.

[0051] 204. Take a calculation result of a preset loss function as an adjustment target, adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold. Wherein the loss function is used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence.

[0052] 205. Determining that the deep learning model has been trained after the calculation result of the loss function converges and is less than the preset convergence threshold.

[0053] For step 201, before training, the server must first obtain multiple medical image samples for training. These medical image samples can be collected in advance, but it should be noted that the image type of these medical image samples should be consistent with the above-mentioned target medical images, that is, if the target medical image is an OCT image, the medical image sample should also be an OCT image.

[0054] For step 202, in this embodiment, each of the medical image samples is marked with a label sequence in advance, and each element in the label sequence is a label value corresponding to each of the preset lesion types, wherein the label value corresponding to the positive preset lesion type is 1, and the label value corresponding to the negative preset lesion type is 0. For example, suppose a medical image sample has been identified by a medical expert, and the medical image sample shows that it has a lesion of "Intraretinal effusion". Suppose there are 4 preset lesion types, followed by "Pigment epithelial detachment", "Intraretinal effusion", "Drusen" and "Macular epiretinal membrane", the label sequence of the medical image sample can be recorded as "0100".

[0055] It can be seen that the elements in the label sequence correspond to the preset

lesion types through a fixed position, and the value of the element could be 0 or 1, wherein 0 indicates that the preset lesion type is negative, and 1 indicates that the preset lesion type is positive.

[0056] For step 203, further, referring to FIG. 4, the deep learning model sequentially includes a preset first number of Dense Blocks and a fully connected layer, wherein a convolutional layer and a pooling layer are provided between any two adjacent Dense Blocks. A convolutional layer and a global average pooling layer are provided between the last Dense Block and the fully connected layer. The fully connected layer includes a preset second number of network units, and the preset second number is equal to the number of the preset lesion types. It should be noted that the deep learning model shown in FIG. 4 specifically provided with 4 Dense Blocks. In actual use, the number of Dense Blocks can be increased or decreased according to actual conditions.

[0057] Based on the above network structure of the deep learning model, step 203 may specifically be: for each of the medical image samples, before inputting it into the deep learning model, first perform vectorization processing on the medical image sample, and perform convolution processing to reduce dimensionality. Then input the vector with reduced dimensionality to the first Dense Block. The first Dense Block performs multi-layer densely connected nonlinear transformation processing on the input vector, then performs convolution and pooling processing on the processed results, and then put it into the second Dense Block for processing; similarly, perform convolution and pooling processing on the results obtained by the second Dense Block, and then put it into the third Dense Block for processing, and so on, until the last Dense Block (as shown in FIG. 4, is the fourth Dense Block) is processed, the processed results are convolved and global average pooled, and then the resulting vector is put into the fully connected layer for classification and recognition, and the value output by each network unit in the fully connected layer is obtained, which is the second confidence, that is, each element in the sample sequence, and these elements constitute the sample sequence.

[0058] For each Dense Block in the deep learning model, after the vector is input into

the Dense Block, the Dense Block contains multiple densely connected processing layers. Each processing layer can be represented by a nonlinear transformation function $H_l(\cdot)$, denote the output of the l -th processing layer is x_l , then $x_l = H_l([x_0, x_1, \dots, x_{l-1}])$, wherein $[x_0, x_1, \dots, x_{l-1}]$ represents the output of the 0-th, ..., (l-1)-th processing layer. It can be understood that the nonlinear transformation $H_l(\cdot)$ in this embodiment may specifically be a composite function of three continuous operations of Batch Normalization (BN), ReLU, and Convolution (Conv).

[0059] For the above fully connected layer, each network unit in the fully connected layer outputs a confidence a . The formula is expressed as $a = \delta(wx + b)$, wherein x is the input of the fully connected layer, and w and b are respectively the weight and bias of the network unit, δ is specifically the sigmoid function $\delta(x) = 1/(1 + e^{-x})$.

[0060] For the above step 203, it should be noted that when training the deep learning model, all medical image samples need to be repeatedly input into the deep learning model for training, that is, iterative training is performed. The model parameter adjustment of the deep learning model is completed in the iterative process. It can be seen that the iterative training process of the deep learning model is combined with step 204 for processing. After each iterative training is completed, step 204 is executed to determine whether the calculation result of the loss function has converged, so that it can be known whether the deep learning model has been trained.

[0061] For step 204, it can be seen from the above that, in the process of iterative training of the deep learning model, the server takes the calculation result of the preset loss function as an adjustment target, and adjusts the model parameters of the deep learning model until the calculation result of the loss function converges and is less than the preset convergence threshold. Wherein, the loss function may specifically be a binary cross-entropy loss function. Wherein, the preset convergence threshold can be set according to actual usage, for example, it can be set to 0.005. Generally speaking, the preset convergence threshold should be small enough to ensure that the calculation result of the loss function is small enough, so that the difference between the model output value and

the label value is within an acceptable range.

[0062] When adjusting the model parameters, the Adam optimization method can be used to optimize the training process of the model, and the learning rate of the training can be set to $lr=0.0001$. The Adam optimization method automatically adjusts the model parameters of the deep learning model according to the calculation results of the loss function during this iterative training. After adjusting the model parameters, enter the next iterative training process and calculate the result of the loss function, so that the next model parameter adjustment is performed again. After such repeated iterative training and model parameter adjustment, the calculation result of the loss function can finally converge and be less than the preset convergence threshold. At this time, it can be determined that the deep learning model has been trained.

[0063] In addition, optionally, the input order of the medical image samples can be randomly disrupted during the training process to obtain a better iterative training effect.

[0064] For step 205, it can be known that after the calculation result of the loss function converges, the server can determine that the deep learning model has been trained.

[0065] 103. After inputting the target medical image into the deep learning model, extract the first feature map output by the last convolutional layer in the deep learning model;

[0066] With reference to FIG. 4, it can be seen that the last layer of the convolutional layer in the deep learning model outputs a vector feature map, and the server can extract the vector feature map as the first feature map described above.

[0067] 104. Extract a weight value of each network unit corresponding to each of the preset lesion types in the fully connected layer of the deep learning model.

[0068] The fully connected layer of the deep learning model contains multiple network units, the number of which is equal to the number of the preset lesion types and is used to classify and recognize the vector feature map input to the fully connected layer. Therefore, it can be understood that the weight value adjusted in advance during training in each

network unit can be considered as a quantification of the importance of the corresponding preset lesion type on the vector feature map. Therefore, the server may extract the weight value of each network unit corresponding to each of the preset lesion types in the fully connected layer of the deep learning model.

[0069] 105. For each of the preset lesion types, calculate a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types.

[0070] After the server obtains the first feature map and the weight value of each network unit, for each of the preset lesion types, a fusion feature map corresponding to each of the preset lesion types is calculated according to the weight value corresponding to the first feature map and each of the preset lesion types.

[0071] Further, step 105 may specifically be: for each of the preset lesion types, substituting the first feature map and the weight value corresponding to each of the preset lesion types into a preset weighted sum formula, to calculate and obtain the weight value of each of the preset lesion types. Fusion feature map corresponding to the preset lesion types;

[0072] The weighted sum formula is:

$$F_c = \sum_{k=1}^K w_k^c \cdot f_k$$

[0073]

[0074] Wherein, F_c is a vector value of the fusion feature map, K is the number of extracted first feature maps, c is the serial number of the preset lesion type, f_k represents the k -th extracted first feature map, and w_k^c represents the weight of the c -th preset lesion type corresponding to the k -th input unit in the fully connected layer.

[0075] It can be seen that on the fusion feature map obtained by calculation, the pixel value of each point reflects the possibility that the point belongs to the preset lesion type,

the larger the pixel value, the greater the possibility.

[0076] 106. Resample the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generate a generic activation map corresponding to each of the preset lesion types.

[0077] In order to keep the size of the fusion feature map consistent with the target medical image, the server may resample the fusion feature map corresponding to each of the preset lesion types until it is consistent with the size of the target medical image, and generate a generic activation map corresponding to each of the preset lesion types, so that the border determined subsequently in the generic activation map is suitable for the target medical image.

[0078] 107. Determine a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establish a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls.

[0079] In this embodiment, a designated pixel threshold may be preset, and the designated pixel threshold is used as a boundary value defining a point belonging to the lesion area in the generic activation map. Therefore, the server can determine the maximum connected area in the generic activation map corresponding to each of the preset lesion types and establish a marked border encircling the maximum connected area. Wherein, the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls. It is understandable that the maximum connected area is surrounded by the marked border, and the maximum connected area is composed of points that meet the condition (that is, the pixel value exceeds the specified pixel threshold). Therefore, it can be considered that the maximum connected area is the lesion area of the preset lesion type, and the marked border also marks the lesion area from the generic activation map.

[0080] It should be noted that the specified pixel threshold can be set manually or can be set according to the maximum pixel value on the generic activation map, for example, set to 20% of the maximum pixel value.

[0081] For ease of understanding, the following will describe in detail how to determine the maximum connected area from the generic activation map and establish the content of the marked border. Further, as shown in FIG. 5, step 107 may comprise the steps of:

[0082] 301. Obtain the maximum pixel value of a point on the generic activation map for the generic activation map corresponding to each of the preset lesion types.

[0083] 302. Calculate the product of the maximum pixel value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1.

[0084] 303. Establish an initial border, and adjust the initial border to minimize the area encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold.

[0085] 304. Detect a maximum connected area within the area encircled by the initial border.

[0086] 305. Establish a marked border and adjust the marked border to minimize the area encircled by the marked border, the marked border encircling the maximum connected area.

[0087] First of all, it should be noted that the subsequent steps are processed separately for the generic activation map corresponding to each of the preset lesion types. Specifically, the server can process multiple generic activation maps simultaneously in a multi-threaded manner, and one generic activation map is calculated and processed by one thread; it is also possible to perform the above steps 301-305 on each generic activation map in a single-threaded manner, which is not limited in this embodiment.

[0088] For step 301, for the generic activation map corresponding to each of the preset

lesion types, the server may obtain the maximum pixel value of the point on the generic activation map, that is, the maximum value among the pixel values of all points.

[0089] For step 302, a preset ratio value may be preset, and after obtaining the maximum pixel value, the server may calculate the product of the maximum pixel value and the preset ratio value to obtain the boundary pixel threshold. Wherein, the preset ratio value is greater than 0 and less than 1, for example, it can be set to 0.2 or 20%.

[0090] For step 303, after the boundary pixel threshold is calculated, the server may first establish an initial border, which encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold. Then, the initial border is adjusted to minimize the area encircled by the initial border, which is equivalent to the smallest border that can encircle all the above points.

[0091] For step 304, after determining the minimized initial border, the server may detect the maximum connected area within the area encircled by the initial border. It is understandable that the representation of the lesion on the image should be a whole connected area, and in the area defined by the initial border, the maximum connected area must be the lesion area. Therefore, detecting the maximum connected area is equivalent to finding out of the lesion area.

[0092] It should be noted that there are many ways to detect the maximum connected area. For example, the function `bwlabel` in matlab to solve the connected area of the image can be used, the `findContours` function in OpenCV is also can be used, and so on, which is not limited in this embodiment.

[0093] For step 305, after detecting the maximum connected area, the server may establish a marked border that surrounds the maximum connected area, and then adjust the marked border to minimize the area encircled by the marked border. Thereby, a minimum marked border encircling the maximum connected area can be obtained, and the marked border plays a role in marking the lesion area.

[0094] Specifically, the initial border and the marked border in this embodiment may be a rectangular border, or other polygonal border, or even an irregular border.

[0095] 108. Add the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

[0096] After the marked border is established, it can be understood that since the generic activation map has the same size as the target medical image and comes from the target medical image, the area selected by the marked border on the generic activation map is also the area where the lesion is positioned on the target medical image. Therefore, the server may add the marked border corresponding to the preset lesion type on the target medical image, thereby completing the marking of the preset lesion type. In the same way, the server establishes the marked borders of each of the preset lesion types and adds them to the same target medical image, and then all the lesion areas on the target medical image can be selected with the marked borders, so as to achieve the detection and positioning of the lesion area.

[0097] Considering that the server performs step 102 to obtain each first confidence, these first confidences only represent the probability that the target medical image belongs to the corresponding preset lesion type, and it is difficult for the user to directly know whether the target medical image has lesions and what lesion types from these first confidences. Therefore, in this embodiment, the confidence threshold can also be preset. After each first confidence is obtained, the preset confidence threshold can be used to determine which lesions in the target medical image are positive and which lesions are negative, so as to facilitate the users to consult and obtain classification results. Further, as shown in FIG. 6, after step 102, the method further includes:

[0098] 401. Obtain a preset confidence threshold corresponding to each of the preset lesion types.

[0099] 402. Compare each element in the target sequence with a corresponding preset confidence threshold, to determine an element in the target sequence that is greater than

or equal to the preset confidence threshold and recorded as a target element.

[00100] 403. Determine a prediction result of the preset lesion type corresponding to each target element on the target medical image as positive and determine a prediction result of the preset lesion type corresponding to other elements on the target medical image as negative. The other elements refer to elements other than the target element in the target sequence.

[00101] For step 401, in this embodiment, the preset confidence thresholds corresponding to various preset lesion types may be preset on the server, and the server may obtain these preset confidence thresholds when necessary.

[00102] It is understandable that these preset confidence thresholds can be artificially set based on empirical values, or they can be predetermined through samples. The method of predetermining the preset confidence threshold through samples will be described in detail below.

[00103] Furthermore, as shown in FIG. 7, the preset confidence threshold corresponding to each of the preset lesion types is predetermined through the following steps:

[00104] 501. Obtain each medical image collected in advance for verification, and record it as each verification sample;

[00105] 502. For each verification sample, input each verification sample to the pre-trained deep learning model to obtain a verification sequence output by the deep learning model and corresponding to each verification sample. Wherein, each element in the verification sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type;

[00106] 503. For each of the preset lesion types, extract the third confidence corresponding to each of the preset lesion types in the verification sequence corresponding to each verification sample, to obtain a lesion confidence;

[00107] 504. For each preset lesion type, respectively calculate a Youden index when the lesion confidence is used as a threshold according to the lesion confidence, to obtain an index result corresponding to the lesion confidence;

[00108] 505. Determine the lesion confidence corresponding to a maximum index result as the preset confidence threshold corresponding to each of the preset lesion types. The maximum index result refers to a maximum value of the index results corresponding to the lesion confidence.

[00109] For step 501, similar to the above step 201, some medical images can be collected in advance as samples for verification and recorded as each verification sample.

[00110] For step 502, for each verification sample, the server may input each verification sample to the pre-trained deep learning model to obtain the verification sequence output by the deep learning model and corresponding to each verification sample. Wherein, each element in the verification sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type. The processing process of each verification sample in the deep learning model is the same as the above content and will not be repeated here.

[00111] For step 503, it can be understood that, assuming that N verification samples are input into the deep learning model, N verification sequences are obtained by step 502. Therefore, for each of the preset lesion types, the server can extract the third confidence corresponding to the preset lesion type from the N verification sequences, and extract a total of N third confidences, that is, N lesion confidences.

[00112] For step 504, for each of the preset lesion types, after obtaining the N lesion confidences corresponding to the preset lesion type, the server may determine each of the lesion confidence as a threshold, and for each threshold, the Youden index of the lesion confidence is calculated to obtain an index result corresponding to the threshold. It can be seen that assuming a total of the lesion confidences being N , there are N thresholds in total,

and one index result is calculated for each threshold. Therefore, N thresholds are calculated to obtain N index results respectively.

[00113] For example, suppose that for a certain preset lesion type, the N lesion confidences obtained by the server is recorded as $l=\{l_1, l_2, l_3, \dots\}$; the Youden index is calculated when $l_1, l_2, l_3, \dots$ are respectively used as thresholds for prediction. The detailed steps are as follows:

[00114] Use l_1 as a threshold to predict each verification sample, and get the prediction result of each verification sample (a confidence greater than or equal to l_1 is positive, and less than l_1 is negative); the prediction result is compared with the labeled result of the verification sample, and the number of samples of True Positive, False Positive, True Negative, and False Negative are counted to calculate the TPR (True Positive Rate) and TNR (False Positive Rate) values. The Youden index, when l_1 is used as the threshold, is calculated by using the formula $TPR+TNR-1$ and denoted as y_1 ; similarly, the Youden index $y_2, y_3, \dots, y_n$, when $l_2, l_3, \dots$ are used as the threshold for prediction, are respectively calculated.

[00115] For step 505, the N index results are compared, and the lesion confidence corresponding to the largest value in the index results is taken as the preset confidence threshold corresponding to the preset lesion type. It is understandable that the Youden index is an indicator for evaluating the authenticity of the screening test. The larger the index, the better the effect of the screening experiment, that is, the more reliable the corresponding confidence and the greater the authenticity. Therefore, it can be considered that the lesion confidence corresponding to the maximum value of the Youden index is a reliable boundary value of the confidence.

[00116] It can be seen from the above content that the above steps are performed for each of the preset lesion types to obtain the preset confidence threshold corresponding to each of the preset lesion types.

[00117] For step 402, the confidence in this embodiment represents a probability that the

medical image belongs to the corresponding preset lesion type, that is, a probability that the preset lesion type is positive in the medical image. Therefore, the server compares each element in the target sequence with the corresponding preset confidence threshold. If an element is larger than the corresponding preset confidence threshold, it means that the preset lesion type corresponding to the element is positive; otherwise, it means that the preset lesion type corresponding to the element is negative. In this embodiment, an element in the target sequence that is greater than or equal to the preset confidence threshold may be determined as the target element.

[00118] For step 403, it can be seen from the above that the server can determine that the prediction result of the preset lesion type corresponding to each target element in the target medical image is positive and determine that the prediction result of the preset lesion type corresponding to other elements in the target medical image is negative, wherein the other elements refer to elements other than the target element in the target sequence.

[00119] In the embodiment of the present application, firstly, the target medical image of the lesion to be detected is obtained; then, the target medical image is input into a pre-trained deep learning model to obtain the target sequence output by the deep learning model. Each element in the target sequence is a first confidence corresponding to each of the preset lesion types, and the first confidence represents a probability that the target medical image belongs to the corresponding preset lesion type. The deep learning model is obtained by pre-training the medical image samples corresponding to each of the preset lesion types, and each medical image sample is marked with the lesion type contained in the image. After the target medical image is input to the deep learning model, the first feature map output by the last convolutional layer in the deep learning model is extracted; and the weight value of each network unit corresponding to each of the preset lesion types in the fully connected layer of the deep learning model is extracted ; then, for each of the preset lesion types, according to the first feature map and the weight value corresponding to each of the preset lesion types, the fusion feature map corresponding to each of the preset lesion types is calculated; furthermore, the fusion feature map corresponding to

each of the preset lesion types is resampled to the same size as the target medical image, and a generic activation map corresponding to each of the preset lesion types is generated; after that, the maximum connected area in the generic activation map corresponding to each of the preset lesion types is determined, and a marked border encircling the maximum connected area is established. The maximum connected area refers to the connected area in which the pixel value of the generic activation map exceeds the specified pixel threshold; finally, a marked border corresponding to each of the preset lesion types is added to the target medical image as the positioning result of the lesion to be detected. It can be seen that the deep learning model trained by the present application does not need to label precise lesion location information, but only needs to label the lesion type contained in each sample, which greatly reduces the workload of labeling and improves the ability of the deep learning model to quickly update and learn. In addition, the present application can not only classify and recognize the lesion types in the target medical image through the deep learning model, but also detect and locate the lesion in the target medical image through the first feature map generated during the deep learning model recognition process, and it is marked in the form of a border to realize the detection and positioning of the medical image lesion.

[00120] It should be understood that the size of the sequence number of each step in the foregoing embodiment does not mean the order of execution, and the execution sequence of each process should be determined by its function and internal logic, and should not constitute any limitation to the implementation process of the embodiment of the present application.

[00121] In an embodiment, a device for detecting and positioning a medical image lesion is provided, and the device for detecting and positioning a medical image lesion corresponds to the method for detecting and positioning a medical image lesion in the above-mentioned embodiment in a one-to-one correspondence. As shown in FIG. 8, the device for detecting and positioning a medical image lesion includes a medical image obtaining module 601, an image input module 602, a first feature map extraction module

603, a weight value extraction module 604, a fusion feature map calculation module 605, a generic activation map generation module 606, a connected area determination module 607, and a marked border adding module 608. The detailed description of each functional module is as follows:

[00122] The medical image obtaining module 601 is configured to obtain a target medical image of a lesion to be detected.

[00123] The image input module 602 is configured to input the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image.

[00124] The first feature map extraction module 603 is configured to extract a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model.

[00125] The weight value extraction module 604 is configured to extract the weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model.

[00126] The fusion feature map calculation module 605 is configured to, for each of the preset lesion types, calculate a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types.

[00127] The generic activation map generating module 606 is configured to resample the fusion feature map corresponding to each of the preset lesion types to the same size as the

target medical image, and generating a generic activation map corresponding to each of the preset lesion types.

[00128] The connected area determination module 607 is configured to determine a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls.

[00129] The marked border adding module 608 is configured to add the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

[00130] As shown in Figure 9, further, the deep learning model can be pre-trained by the following modules:

[00131] A image sample obtaining module 609, configured to obtain multiple medical image samples for training;

[00132] A labeling module 610, configured to mark a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical image samples,,for each of the medical image samples; wherein each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0;

[00133] An iterative training module 611, configured to input each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples, for each of the labeled medical image samples; wherein each element in the sample sequence is a second confidence corresponding to each of the preset lesion types, and the second confidence represents a probability that each of the medical image samples belongs to a

corresponding preset lesion type;

[00134] A parameter adjustment module 612, configured to take a calculation result of a preset loss function as an adjustment target, and adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold, and the loss function being used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence;

[00135] A model determination module 613, configured to determine that the deep learning model has been trained, after the calculation result of the loss function converges and is less than the preset convergence threshold.

[00136] As shown in FIG. 10, further, the connected area determining module 607 may include:

[00137] The pixel value obtaining unit 6071, configured to obtain the maximum pixel value of a point on the generic activation map for the generic activation map corresponding to each of the preset lesion types;

[00138] The pixel threshold calculation unit 6072, configured to calculate the product of the maximum pixel value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1;

[00139] The border establishment and adjustment unit 6073, configured to establish an initial border, and adjusting the initial border to minimize the area encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold;

[00140] The connected area detection unit 6074, configured to detect a maximum connected area within the area encircled by the initial border;

[00141] The encircling area minimizing unit 6075, configured to establish a marked border and adjusting the marked border to minimize the area encircled by the marked

border, the marked border encircling the maximum connected area.

[00142] Further, the device for detecting and positioning a medical image lesion may further include:

[00143] A confidence threshold obtaining module, configured to obtain a preset confidence threshold corresponding to each of preset lesion types;

[00144] A comparison module, configured to compare each element in the target sequence with a corresponding preset confidence threshold, to determine an element in the target sequence that is greater than or equal to the preset confidence threshold and is recorded as a target element;

[00145] A prediction result determining module, configured to determine a prediction result of the preset lesion type corresponding to each target element on the target medical image as positive, and determining a prediction result of the preset lesion type corresponding to other elements on the target medical image as negative, and the other elements referring to elements other than target element in the target sequence.

[00146] Further, the preset confidence threshold corresponding to each of the preset lesion types may be predetermined by the following modules:

[00147] A verification sample obtaining module, configured to obtain each medical image collected in advance for verification, and record it as each verification sample;

[00148] A sample input module, configured to input each each verification sample to the pre-trained deep learning model to obtain a verification sequence output by the deep learning model and corresponding to each verification sample, for each verification sample; wherein each element in the verification sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type;

[00149] A lesion confidence extraction module, configured to extract, for each of the preset lesion types, the third confidence corresponding to each of the preset lesion types

in the verification sequence corresponding to each verification sample to obtain a lesion confidence;

[00150] A index result calculation module, configured to calculate Youden index when the lesion confidence is used as a threshold according to the lesion confidence, to obtain an index result corresponding to the lesion confidence, for each of the preset lesion types;

[00151] A threshold determination module, configured to determine the lesion confidence corresponding to a maximum index result as the preset confidence threshold corresponding to each of the preset lesion types, and the maximum index result referring to a maximum value of the index results corresponding to the lesion confidence.

[00152] Regarding the specific limitation of the device for detecting and positioning a medical image lesion, please refer to the above limitation on the method for detecting and positioning a medical image lesion, which will not be repeated here. Each module in the above-mentioned device for detecting and positioning a medical image lesion can be implemented in whole or in part by software, hardware and a combination thereof. The foregoing modules may be embedded in the form of hardware or independent of the processor in the computer equipment or may be stored in the memory of the computer equipment in the form of software, so that the processor can call it to execute the operations corresponding to the foregoing modules.

[00153] In an embodiment, a computer equipment is provided. The computer equipment may be a server, and its internal structure diagram may be as shown in FIG. 11. The computer equipment includes a processor, a memory, a network interface and a database all connected by a system bus. Wherein, the processor of the computer equipment is used to provide calculation and control capabilities. The memory of the computer equipment includes a readable storage medium and an internal memory. The readable storage medium stores an operating system, computer readable instructions, and a database. The internal memory provides an environment for the operation of the operating system and computer readable instructions in the readable storage medium. The database of the

computer equipment is used to store the data involved in the method for detecting and positioning a medical image lesion. The network interface of the computer equipment is used to communicate with an external terminal through a network connection. When the computer readable instruction is executed by the processor, a method for detecting and positioning a medical image lesion is realized. The readable storage medium provided in this embodiment includes a nonvolatile readable storage medium and a volatile readable storage medium.

[00154] In an embodiment, a computer equipment is provided, including a memory, a processor, and computer readable instructions stored in the memory and run in the processor. When the processor executes the computer readable instructions, the steps of the method for detecting and positioning a medical image lesion in the foregoing embodiment is implemented, for example, step 101 to step 108 shown in FIG. 2. Alternatively, when the processor executes the computer readable instructions, the functions of the modules/units of the device for detecting and positioning a medical image lesion in the foregoing embodiment are implemented, for example, the functions of the modules 601 to 608 shown in FIG. 8. To avoid repetition, it will not be repeated here.

[00155] In an embodiment, a computer readable storage medium is provided. The one or more computer readable storage media stores computer readable instructions. When the computer readable instructions are executed by one or more processors, one or more processors execute the computer readable instructions to implement the steps of the method for detecting and positioning a medical image lesion in the above method embodiment. Alternatively, the one or more readable storage media stores computer readable instructions, when the computer readable instructions are executed by one or more processors, one or more processors execute the computer readable instructions to implement the functions the modules/units of the device for detecting and positioning a medical image lesion in the foregoing embodiment. To avoid repetition, it will not be repeated here. The readable storage medium provided in this embodiment includes a nonvolatile readable storage medium and a volatile readable storage medium.

[00156] The above-mentioned embodiments are only used to illustrate the technical solutions of the present application, but not to limit them; although the embodiments of the present application are described in detail with reference to the foregoing embodiments, those of ordinary skill in the art should understand that it is still possible to modify the technical solutions recorded in the foregoing embodiments, or equivalently replace some of the technical features; and these modifications or replacements do not cause the essence of the corresponding technical solutions to deviate from the spirit and scope of the technical solutions of the embodiments of the present application, and should be included in the protection scope of the embodiments of the present application.

What is claimed is:

1. A method for detecting and positioning a medical image lesion, comprising:
 - obtaining a target medical image of a lesion to be detected;
 - inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image;
 - extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;
 - extracting a weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model;
 - for each of the preset lesion types, calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types;
 - resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;
 - determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and
 - adding the marked border corresponding to each of the preset lesion types on the target

medical image as a positioning result of the lesion to be detected.

2. The method for detecting and positioning a medical image lesion as claimed in claim 1, wherein the deep learning model is pre-trained by the steps of:

obtaining multiple medical image samples for training;

for each of the medical image samples, marking a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical image samples, wherein each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0;

for each of the labeled medical image samples, inputting each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples; wherein each element in the sample sequence is a second confidence corresponding to each of the preset lesion types, and the second confidence represents a probability that each of the medical image samples belongs to a corresponding preset lesion type;

taking a calculation result of a preset loss function as an adjustment target, adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold, and the loss function being used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence;

after the calculation result of the loss function converges and is less than the preset convergence threshold, determining that the deep learning model has been trained.

3. The method for detecting and positioning a medical image lesion as claimed in claim 1, wherein the step of determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area comprise:

obtaining a maximum pixel value of the point on the generic activation map for the generic activation map corresponding to each of the preset lesion types;

calculating the product of the maximum pixel value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1;

establishing an initial border, and adjusting the initial border to minimize the area encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold;

detecting a maximum connected area within the area encircled by the initial border;

establishing a marked border and adjusting the marked border to minimize the area encircled by the marked border, the marked border encircling the maximum connected area.

4. The method for detecting and positioning a medical image lesion as claimed in claim 1, wherein after the step of inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, the method further comprises:

obtaining a preset confidence threshold corresponding to each of preset lesion types;

comparing each element in the target sequence with a corresponding preset confidence threshold, to determine an element in the target sequence that is greater than or equal to the preset confidence threshold and is recorded as a target element;

determining a prediction result of the preset lesion type corresponding to each target element on the target medical image as positive, and determining a prediction result of the preset lesion type corresponding to other elements on the target medical image as negative, and the other elements referring to elements other than target element in the target sequence.

5. The method for detecting and positioning a medical image lesion as claimed in claim

4, wherein the preset confidence threshold corresponding to each of preset lesion types is predetermined by the steps of:

obtaining each medical image collected in advance for verification and recording it as each verification sample;

for each verification sample, inputting each verification sample to the pre-trained deep learning model to obtain a verification sequence output by the deep learning model and corresponding to each verification sample, wherein each element in the verification sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type;

for each of the preset lesion types, extracting the third confidence corresponding to each of the preset lesion types in the verification sequence corresponding to each verification sample to obtain a lesion confidence;

for each of the preset lesion types, calculating a Youden index when the lesion confidence is used as a threshold according to the lesion confidence, to obtain an index result corresponding to the lesion confidence;

determining the lesion confidence corresponding to a maximum index result as the preset confidence threshold corresponding to each of the preset lesion types, and the maximum index result referring to a maximum value of the index results corresponding to the lesion confidence.

6. The method for detecting and positioning a medical image lesion as claimed in claim 2, wherein before the step of inputting each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples, the method further comprises:

randomly disrupting the order in which the labeled medical image samples are input to the deep learning model.

7. The method for detecting and positioning a medical image lesion as claimed in anyone of claims 1 to 6, wherein the step of for each of the preset lesion types, calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types comprise:

for each of the preset lesion types, substituting the weight value corresponding to the first feature map and each of the preset lesion types into a preset weighted sum formula, to calculate and obtain a fusion feature map corresponding to each of the preset lesion types;

the weighted sum formula is:

$$F_c = \sum_{k=1}^K w_k^c \cdot f_k$$

wherein, F_c is a vector value of the fusion feature map, K is the number of extracted first feature maps, c is the serial number of the preset lesion type, f_k represents the k -th extracted first feature map, and w_k^c represents the weight of the c -th preset lesion type corresponding to the k -th input unit in the fully connected layer.

8. A device for detecting and positioning a medical image lesion, comprises:

a medical image obtaining module, for obtaining a target medical image of a lesion to be detected;

an image input module, for inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the

image;

a first feature map extraction module, for extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;

a weight value extraction module, for extracting a weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model;

a fusion feature map calculation module, for calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types, for each of the preset lesion types;

a generic activation map generation module, for resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;

a connected area determination module, for determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and

a marked border adding module, for adding the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

9. The device for detecting and positioning a medical image lesion as claimed in claim 8, wherein the deep learning model is pre-trained by the following modules:

an image sample obtaining module, for obtaining multiple medical image samples for training;

a labeling module, for marking a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical image samples,,for each of the medical image samples; wherein each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0;

an iterative training module, for inputting each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples, for each of the labeled medical image samples; wherein each element in the sample sequence is a second confidence corresponding to each of the preset lesion types, and the second confidence represents a probability that each of the medical image samples belongs to a corresponding preset lesion type;

a parameter adjustment module, for taking a calculation result of a preset loss function as an adjustment target, and adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold, and the loss function being used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence; and

a model determination module, for determining that the deep learning model has been trained, after the calculation result of the loss function converges and is less than the preset convergence threshold.

10. The device for detecting and positioning a medical image lesion as claimed in claim 8, wherein the connected area determination module comprises:

a pixel value obtaining unit, for obtaining a maximum pixel value of the point on the generic activation map for the generic activation map corresponding to each of the preset lesion types;

a pixel threshold calculation unit, for calculating the product of the maximum pixel

value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1;

a border establishment and adjustment unit, for establishing an initial border, and adjusting the initial border to minimize the area encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold;

a connected area detection unit, for detecting a maximum connected area within the area encircled by the initial border; and

an encircling area minimizing unit, for establishing a marked border and adjusting the marked border to minimize the area encircled by the marked border, the marked border encircling the maximum connected area.

11. The device for detecting and positioning a medical image lesion as claimed in claim 8, wherein the device for detecting and positioning a medical image lesion further comprises:

a confidence threshold obtaining module, for obtaining a preset confidence threshold corresponding to each of preset lesion types;

a comparison module, for comparing each element in the target sequence with a corresponding preset confidence threshold, to determine an element in the target sequence that is greater than or equal to the preset confidence threshold and is recorded as a target element; and

a prediction result determining module, for determining a prediction result of the preset lesion type corresponding to each target element on the target medical image as positive, and determining a prediction result of the preset lesion type corresponding to other elements on the target medical image as negative, and the other elements referring to elements other than target element in the target sequence.

12. The device for detecting and positioning a medical image lesion as claimed in claim 11, wherein the preset confidence threshold corresponding to each of preset lesion

types is predetermined by the following modules:

a verification sample obtaining module, for obtaining each medical image collected in advance for verification and recording it as each verification sample;

a sample input module, for inputting each verification sample to the pre-trained deep learning model to obtain a verification sequence output by the deep learning model and corresponding to each verification sample, for each verification sample; wherein each element in the verification sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type;

a lesion confidence extraction module, for extracting the third confidence corresponding to each of the preset lesion types in the verification sequence corresponding to each verification sample to obtain a lesion confidence, for each of the preset lesion types;

an index result calculation module, for calculating a Youden index when the lesion confidence is used as a threshold according to the lesion confidence, to obtain an index result corresponding to the lesion confidence, for each of the preset lesion types; and

a threshold determination module, for determining the lesion confidence corresponding to a maximum index result as the preset confidence threshold corresponding to each of the preset lesion types, and the maximum index result referring to a maximum value of the index results corresponding to the lesion confidence.

13. A computer equipment, comprising a memory, a processor, and computer readable instructions stored in the memory and run in the processor, wherein the processor executes the computer readable instructions to implement the steps of:

obtaining a target medical image of a lesion to be detected;

inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target

sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image;

extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;

extracting a weight value of each network unit corresponding to each of the preset lesion types in fully connected layer of the deep learning model;

for each of the preset lesion types, calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types;

resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;

determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and

adding the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

14. The computer equipment as claimed in claim 13, wherein the deep learning model is pre-trained by the steps of:

obtaining multiple medical image samples for training;

for each of the medical image samples, marking a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical

image samples, wherein each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0;

for each of the labeled medical image samples, inputting each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples; wherein each element in the sample sequence is a second confidence corresponding to each of the preset lesion types, and the second confidence represents a probability that each of the medical image samples belongs to a corresponding preset lesion type;

taking a calculation result of a preset loss function as an adjustment target, adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold, and the loss function being used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence;

after the calculation result of the loss function converges and is less than the preset convergence threshold, determining that the deep learning model has been trained.

15. The computer equipment as claimed in claim 13, wherein the step of determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area comprise:

obtaining a maximum pixel value of the point on the generic activation map for the generic activation map corresponding to each of the preset lesion types;

calculating the product of the maximum pixel value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1;

establishing an initial border, and adjusting the initial border to minimize the area

encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold;

detecting a maximum connected area within the area encircled by the initial border;

establishing a marked border and adjusting the marked border to minimize the area encircled by the marked border, the marked border encircling the maximum connected area.

16. The computer equipment as claimed in claim 13, wherein after the step of inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, the processor executes the computer readable instructions to further implement the steps of:

obtaining a preset confidence threshold corresponding to each of preset lesion types;

comparing each element in the target sequence with a corresponding preset confidence threshold, to determine an element in the target sequence that is greater than or equal to the preset confidence threshold and is recorded as a target element;

determining a prediction result of the preset lesion type corresponding to each target element on the target medical image as positive, and determining a prediction result of the preset lesion type corresponding to other elements on the target medical image as negative, and the other elements referring to elements other than target element in the target sequence.

17. The computer equipment as claimed in claim 16, wherein the preset confidence threshold corresponding to each of preset lesion types is predetermined by the steps of:

obtaining each medical image collected in advance for verification and recording it as each verification sample;

for each verification sample, inputting each verification sample to the pre-trained deep learning model to obtain a verification sequence output by the deep learning model and corresponding to each verification sample, wherein each element in the verification

sequence is a third confidence corresponding to each of the preset lesion types, and the third confidence represents a probability that each verification sample belongs to the corresponding preset lesion type;

for each of the preset lesion types, extracting the third confidence corresponding to each of the preset lesion types in the verification sequence corresponding to each verification sample to obtain a lesion confidence;

for each of the preset lesion types, calculating a Youden index when the lesion confidence is used as a threshold according to the lesion confidence, to obtain an index result corresponding to the lesion confidence;

determining the lesion confidence corresponding to a maximum index result as the preset confidence threshold corresponding to each of the preset lesion types, and the maximum index result referring to a maximum value of the index results corresponding to the lesion confidence.

18. One or more computer readable storage stored with computer readable instructions, wherein the computer readable instructions executed by one or more processors, one or more processors are caused to implement the steps of:

obtaining a target medical image of a lesion to be detected;

inputting the target medical image into a pre-trained deep learning model to obtain a target sequence output by the deep learning model, wherein each element in the target sequence is a first confidence corresponding to each of preset lesion types, the first confidence represents a probability that the target medical image belongs to a corresponding preset lesion type, the deep learning model is obtained by pre-training medical image samples corresponding to each of the preset lesion types, and each of the medical image samples is labeled with a lesion type contained in the image;

extracting a first feature map output by last convolutional layer in the deep learning model, after inputting the target medical image into the deep learning model;

extracting a weight value of each network unit corresponding to each of the preset

lesion types in fully connected layer of the deep learning model;

for each of the preset lesion types, calculating a fusion feature map corresponding to each of the preset lesion types according to the first feature map and the weight value corresponding to each of the preset lesion types;

resampling the fusion feature map corresponding to each of the preset lesion types to the same size as the target medical image, and generating a generic activation map corresponding to each of the preset lesion types;

determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area, wherein the maximum connected area refers to a connected area in which a point of which pixel value exceeds a specified pixel threshold in the generic activation map falls; and

adding the marked border corresponding to each of the preset lesion types on the target medical image as a positioning result of the lesion to be detected.

19. The readable storage medium as claimed in claim 18, wherein the deep learning model is pre-trained by the steps of:

obtaining multiple medical image samples for training;

for each of the medical image samples, marking a label value corresponding to each of the preset lesion types to obtain a label sequence corresponding to each of the medical image samples, wherein each element in the label sequence is the label value corresponding to each of the preset lesion types, in each of the medical image samples, the label value corresponding to positive preset lesion type is 1, and the label value corresponding to negative preset lesion type is 0;

for each of the labeled medical image samples, inputting each of the medical image samples to a deep learning model for iterative training to obtain a sample sequence output by the deep learning model and corresponding to each of the medical image samples; wherein each element in the sample sequence is a second confidence

corresponding to each of the preset lesion types, and the second confidence represents a probability that each of the medical image samples belongs to a corresponding preset lesion type;

taking a calculation result of a preset loss function as an adjustment target, adjusting a model parameter of the deep learning model until the calculation result of the loss function converges and is less than a preset convergence threshold, and the loss function being used to calculate an error between the sample sequence corresponding to each of the medical image samples and the label sequence;

after the calculation result of the loss function converges and is less than the preset convergence threshold, determining that the deep learning model has been trained.

20. The readable storage medium as claimed in claim 18, wherein the step of determining a maximum connected area in the generic activation map corresponding to each of the preset lesion types, and establishing a marked border encircling the maximum connected area comprise:

obtaining a maximum pixel value of the point on the generic activation map for the generic activation map corresponding to each of the preset lesion types;

calculating the product of the maximum pixel value and a preset ratio value to obtain a boundary pixel threshold, wherein the preset ratio value is greater than 0 and less than 1;

establishing an initial border, and adjusting the initial border to minimize the area encircled by the initial border, wherein the initial border encircles all points on the generic activation map of which pixel value is greater than the boundary pixel threshold;

detecting a maximum connected area within the area encircled by the initial border;

establishing a marked border and adjusting the marked border to minimize the area encircled by the marked border, the marked border encircling the maximum connected area.