Related Applications of Deep Learning Algorithms in Medical Image Fusion Systems

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***Abstract*—As the continuous advancement of medical technology, image fusion technology has also been used in it. However, current medical image fusion systems still have drawbacks such as low image clarity, low accuracy, and slow computing speed. To address this drawback, this study utilized speeded up robust features image recognition algorithms to optimize deep residual network algorithms and proposed an optimization algorithm based on residual network deep learning algorithms. Based on this optimization algorithm, a medical image fusion system was constructed. Comparative experiments were organized on the improved algorithm, and the experiment outcomes denoted that the accuracy of image feature extraction was 0.98, the average time for feature extraction was 0.12 seconds, and the extraction capability was significantly better than that of the comparative algorithms HPF-CNN, PSO and PCA-CNN. Subsequently, experiments were conducted on the image fusion system, and the outcomes denoted that the accuracy and clarity of the fused images were 0.98 and 0.97, respectively, which were superior to other systems. The above outcomes indicate that the proposed medical image fusion system based on optimized deep learning algorithms can not only improve the speed of image fusion, but also enhance the clarity and accuracy of fused images. This study not only improves the accuracy of medical diagnosis, but also provides a theoretical basis for the field of image fusion.**

***Keywords*—Image fusion; image recognition; residual network; medical image; speeded up robust features; medical diagnosis**

I. INTRODUCTION

With the continuous development of computer technology, many fields are using intelligent algorithms to improve work efficiency. In the field of medicine, many intelligent algorithms are used in medical Image Fusion (IF) to improve the clarity of medical IF [1]. To improve image clarity, many scholars have conducted research on medical IF systems, but these IF systems still have problems such as slow speed, low accuracy, and unclear images [2]. So it is necessary to optimize the current medical IF system to improve the accuracy of IF and reduce fusion time. The Residual Neural Network (ResNet) algorithm has the advantages of strong feature extraction ability and improved model accuracy [3]. The Speeded Up Robust Features (SURF) algorithm has the advantages of fast processing speed and high matching accuracy [4]. Therefore, this study utilizes SURF to optimize the ResNet algorithm and proposes an SURF-ResNet algorithm, aiming to accurately extract feature information from medical images through this optimization algorithm, thereby improving the clarity of fused images and accelerating IF speed. The innovation of this study lies in processing medical images through the Hall feature transformation in SURF algorithm and the concept of integrated images, removing irrelevant information, reducing the computational complexity of subsequent ResNet algorithms, and improving computational speed. The contribution of the research lies in optimizing the medical IF system through the SURF-ResNet algorithm, improving image quality, enhancing the accuracy of medical diagnosis, improving clinical decision-making efficiency, and accelerating the speed of doctors' analysis of patients' CT images, saving valuable time for patients. At the same time, personalized treatment can be provided to patients through the IF system, optimizing the use of medical resources.

This study is divided into four sections for discussion. The first section mainly covers the research on medical IF systems, SURF algorithms, and ResNet algorithms. The main content of the second section is the optimization of SURF algorithm on ResNet algorithm and the application of the optimized algorithm in medical IF system. The main content of the third section is the performance analysis of the SURF-ResNet algorithm and the effectiveness analysis of the algorithm in medical IF systems. The fourth section is a summary of the entire text.

II. RELATED WORK

As the continuous advancement of computer technology, computer systems have been introduced in various fields, and IF systems have also been introduced in the field of medical diagnosis. Many domestic and foreign scholars have studied this system. For example, to provide surgical support for corrective osteotomy, Yoshii et al. designed an IF system for three-dimensional preoperative planning and perspective. The system was compared with other systems in experiments, and the results showed that the difference between the fusion reference points of each group was significantly smaller than other systems [5]. The Faragallah team proposed a medical IF system based on resolution, multi-scale transformation, and improved central force technology to solve the deficiencies of poor clarity and weak information detail in medical images. Compared with other systems, it was found that the system improved the clarity of fused images by 78% [6]. Gao et al. put forward a deep learning-based monotonic estimation and IF method to reduce the offset between flight vision system images. The method was compared with other methods and the experiment findings indicated that it reduced the offset

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between images by 70% [7]. El-Shafai et al. designed a medical IF technique based on convolutional neural network to the IF technique in the medical field which still has the problem of low resolution of the fused image. The technique was used in the real situation for detection, and the detection results showed that the technique increased the resolution of the fused image by 56.7% [8].

ResNet algorithm is widely used in various systems due to its strong feature extraction ability and ability to improve model accuracy. SURF algorithm is widely used in various systems due to its simple and stable computation. Many scholars have studied the above algorithms, for example, Sarwinda et al. designed an image classification deep learning method with the ResNet architecture to detect colorectal cancer. This method was contrasted with other methods in experiments, and the outcomes indicated that the method's accuracy was higher than 80%, the sensitivity was higher than 87%, and the specificity was higher than 83% [9]. The Du team designed an evaluation model based on ResNet to address the issue of limited training data evaluation models to small-scale and simplified datasets. The model was contrasted with other models and the findings showed that its correlation coefficient was greater than 0.8, significantly better than other models [10]. To be able to accurately identify the five subtypes of internal cranial haemorrhage and normal images, Zhou's team proposed a ResNet-based deep learning model, which was used in a real-world situation to test the model, and the results showed that the model achieved an overall accuracy of 89.64% [11]. Gupta et al. designed a two-dimensional facial image method with SURF to address the issues of small application databases and multiple variable conditions in facial recognition. Compared with other methods, the outcomes showed that the method's recognition accuracy reached 99.7% [12]. The Fan team designed a target tracking algorithm based on correlation filtering and SURF to address the difficulty of long-term visual target tracking in drones. The algorithm was compared with other algorithms in experiments, and the outcomes showed that the algorithm could rediscover the target after it is blocked or lost, achieving long-term stable target tracking [13]. Ahmed et al. designed an SURF-based image feature extraction method for the problem of high error in target detection methods and compared this method with the traditional target detection methods. The results showed that the proposed method of the study was able to reduce the error in detection [14].

In summary, although many experts and scholars have conducted research on IF systems, these systems still have drawbacks such as low image clarity and slow fusion speed. Therefore, this study will use the SURF algorithm to improve the ResNet algorithm and apply the improved algorithm to medical IF systems to improve the accuracy and clarity of fused images.

III. Methods and Materials

A. *Deep Learning Algorithm Improved by Combining Image Features*

Image is a very important diagnostic criterion in the medical field, but current medical images have the disadvantages of low fusion clarity, low accuracy, artifacts in images, and insufficient feature information extraction [15]. The ResNet algorithm is a special convolutional neural network deep learning algorithm that has better deep network construction compared to traditional neural networks and can improve the accuracy of IF [16]. The basic structure of the ResNet algorithm is indicated in Fig. 1.

As shown in Fig. 1, the ResNet algorithm consists of convolutional layers (CLs), multiple residual blocks, pooling layers (PLs), activation layers, and fully connected layers (FCLs). The residual structure block is composed of CLs, batch normalization, and a Rectified Linear Unit (ReLu) function. The output of the residual block is the sum of the input x and the identity map $f(x)$. The CL is composed of multi-convolution kernels, which are utilized to calculate the feature map of the input image. The calculation principle of CLs is denoted in Eq. (1).

$$x_{i+1} = \sum_{i+1}^{n} x_i \otimes w_i + b_i \tag{1}$$

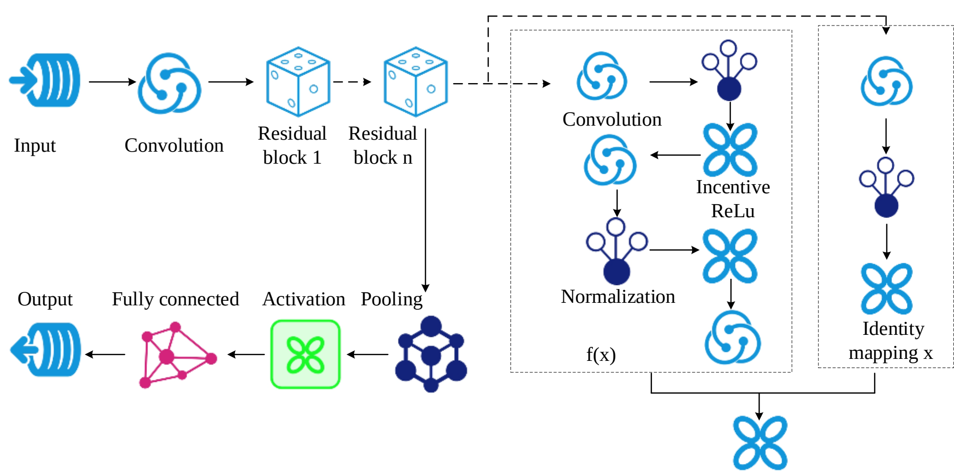


Fig. 1. Basic structure of ResNet algorithm.

In Eq. (1), x_i means the input features of the i th layer. x_{i+1} represents the input features of the $i+1$ th layer CL. $\otimes$ represents the convolution operation. w_i means the weights of the i th layer. b_i means the bias of the i th layer. In the PL, it is broken into maximum pooling and average pooling, and the calculation principle of maximum pooling is shown in Eq. (2).

$$\tilde{m} = \max(m_i, m_{i+r-1}) \tag{2}$$

The principle of average pooling calculation is shown in Eq. (3).

$$\tilde{m} = (m_i + m_{i+1} + \cdots m_{i+r-1}) / r \tag{3}$$

In Eq. (2) and (3), $\tilde{m}$ represents the output feature of the PL. m means the internal sub features of the input feature. r represents the number of sub features. The activation function generally chooses the Relu function, and the function expression is expressed in Eq. (4).

$$\mathrm{Re}\,Lu(x) = \begin{cases} 0, x \le 0 \\ x, x > 0 \end{cases} \tag{4}$$

In Eq. (4), x represents the input feature. The information obtained through convolutional and PLs is input into the FCL, and the forward propagation principle of the FCL is shown in Eq. (5).

$$W_q = \sum_{q=1}^{R} C_{qp} a^{(q)} + b_p \tag{5}$$

In Eq. (5), C_{qp} represents the weight between the q th neuron in the previous layer and the p th neuron in the subsequent layer, while b_p represents the bias value of all neurons in the previous layer towards the p th neuron in the subsequent layer. When outputting the final output, it uses the Softmax function and modifies the classification of feature information. The calculation of the Softmax function is shown in Eq. (6).

$$soft\max(Z_m) = e^{x_m} / \sum_{m=1}^{B} e^{x_m} \tag{6}$$

The calculation method for the output data of the CL after passing through the ResNet is shown in Eq. (7).

$$x_i = f(x_{i-1} + F(x_{i-1}, W_i)) \tag{7}$$

In Eq. (7), $f(\cdot)$ is the nonlinear activation function ReLu, $F(x_{i-1}, W_i)$ means the residual function, and W_i means the weight corresponding to the residual function. The use of ResNet in IF can improve the clarity of IF and the accuracy of image judgment, but this algorithm has high computational difficulty and low computational efficiency. The biggest advantage of the SURF algorithm is the use of Haar-like features (Harr) transformation and the concept of integrated images, which improves the clarity of IF while significantly speeding up program running time [17]. This study optimized the ResNet algorithm using SURF algorithm to improve its computational speed. The basic flowchart of SURF algorithm is shown in Fig. 2 [18].

As shown in Fig. 2, the SURF algorithm mainly consists of three steps: feature space detection, feature descriptor validation, and feature point matching. Feature space detection can be further divided into three steps: integral image calculation, construction of Hessian matrix, and establishment of image pyramid. The effective process of feature descriptor validation consists of three steps: principal direction allocation, feature vector calculation, and normalization. The role of principal direction allocation is to make the feature vector rotationally invariant. Based on this, the feature vector is calculated and then normalized to obtain the final SURF feature descriptor. Feature point matching first involves selecting a feature point, calculating the Euclidean distance, finding neighboring feature points based on the Euclidean distance, and calculating the ratio of the Euclidean distance between two points. If the value is less than the minimum threshold, feature point matching is performed. If it is greater than the minimum threshold, continue to calculate the Euclidean distance, and search for feature points until the algorithm terminates. The definition formula for constructing the Hessian matrix is shown in Eq. (8).

$$H = \begin{bmatrix} L_{aa}(a,b,\sigma) L_{ab}(a,b,\sigma) \\ L_{ab}(a,b,\sigma) L_{bb}(a,b,\sigma) \end{bmatrix} \tag{8}$$

In Eq. (8), (a,b) means the coordinates of a pixel, σ represents the Gaussian scale of the image, and $L(a,b,\sigma)$ represents the convolution of second-order Gaussian differentiation between the pixel (a,b) and the image of that pixel. To accurately identify the local maximum point, SURF uses a box filter to calculate the determinant of the Hessian matrix, as shown in Eq. (9).

$$\det(H) = L_{aa} * L_{bb} - (0.9 * L_{ab})^2 \tag{9}$$

In Eq. (9), the box filtering response value in the area around point (a,b) is represented. The HAR response value of the feature points in each sub block is statistically analyzed to obtain the descriptive operator for each sub block. The calculation method is shown in Eq. (10).

$$D = \left[\sum da, \sum |da|, \sum db, \sum |db| \right] \tag{10}$$

This study combines SURF algorithm with ResNet algorithm to lessen the computational complexity of RestNet algorithm, raise computational efficiency, and thus improve the clarity of fused images. The basic flowchart of the improved deep learning algorithm is shown in Fig. 3.

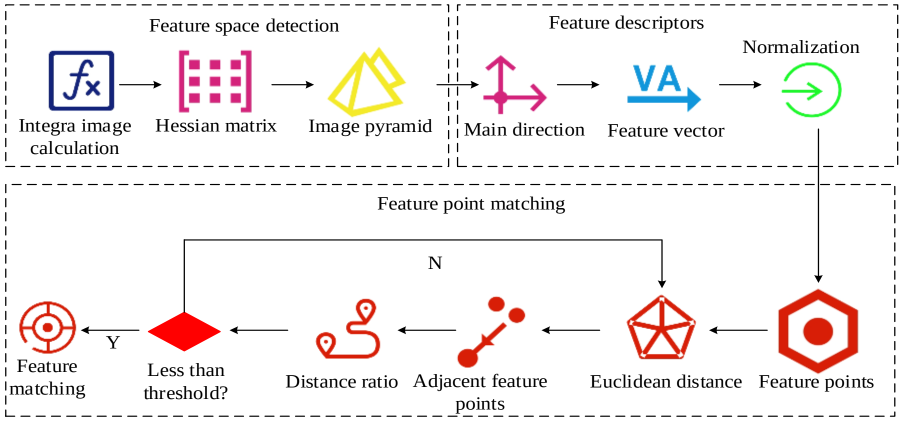


Fig. 2. Basic flowchart of SURF algorithm.

From Fig. 3, the input data information is first received, and then input into the receiving layer of the SURF module. The module preprocesses the input data, extracts the features of the data through feature space detection, feature descriptor validation, and feature point matching. The irrelevant information in the image is initially removed through the SURF module to reduce the complexity of the subsequent calculations to improve the computational efficiency. The image data extracted through this module is input as the input data of ResNet, and the initialised data is then used to extract the image features again through the CL, PL, fully-connected layer and residual network block in the ResNet module, and the extracted information is fused. Finally, the obtained image information is compared with the sample to determine whether its clarity and accuracy meet the requirements. If it meets the requirements, the information is output. If not, the information is returned to the ResNet module for re-extraction of image information.

B. *Application of Optimized Deep Learning Algorithms in Medical Image Fusion Systems*

The SURF-ResNet algorithm can accurately extract image features and fuse the extracted image feature information to comprehensively display information from various dimensions of the image [19]. Currently, there is a need to improve the phenomenon of blurred fused images in medical IF systems. So this study applying the SURF-ResNet algorithm to medical IF systems is expected to improve the phenomenon of image blurring in current medical IF systems. This study utilized the SURF-ResNet algorithm to improve the current medical IF system. The basic flowchart of the improved medical IF system is shown in Fig. 4.

As shown in Fig. 4, during medical IF, medical staff operate the medical IF system, input image capture instructions, and the computer transmits the instructions to the CT device. After receiving the instructions, the CT device console captures the patient according to the instructions and inputs the captured data as the initial dataset into the deep learning model for IF. In this IF model, the SURF module is used to preprocess the image information, deleting irrelevant image information for the first time to reduce subsequent computational complexity. Then, the preprocessed image information is input into the ResNet module, and the features in the patient's CT image are extracted again through the CL, PL, fully connected layer, and residual network block in this module. The extracted features are then fused. Then, it determines whether the image clarity, accuracy, and color meet the standards. If they meet the standards, output them. If not, it will input the image into the deep learning model again for feature extraction until all requirements are met. Finally, the image is printed and output. In this study, a pixel-based IF algorithm was selected for IF, and the calculation method of this algorithm is denoted in Eq. (11).

$$Z(i,j) = \alpha X(i,j) + \beta Y(i,j) \tag{11}$$

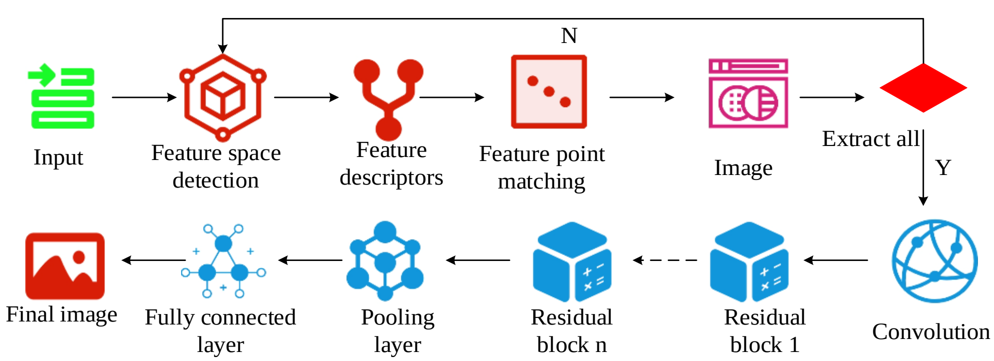


Fig. 3. Flow chart of improved deep learning algorithm.

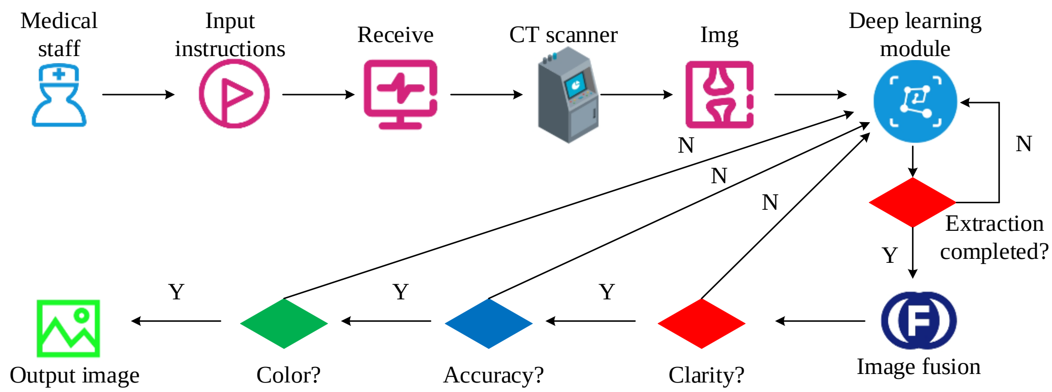


Fig. 4. Medical image fusion system flowchart.

In Eq. (11), X and Y denote different source images that need to be fused, $X(i,j), Y(i,j)$ represents the grayscale value of the source image at (i,j) position, α and β represent the weighting coefficients in the formula, and $\alpha+\beta=1$. The basic framework structure diagram of the feature extraction module and fusion in the system is shown in Fig. 5.

As shown in Fig. 5, this module is broken into SURF layer, ResNet layer, and IF. In the SURF layer, the image information captured by the CT device is received, and the input image information is extracted and filtered in this layer to reduce the computational load of the next layer. Then, the image information is input into the ResNet layer, and the image feature information is further extracted. Finally, the extracted image features are fused to obtain the fused image. After IF, the fusion quality is assessed using mean, average gradient, standard deviation, peak signal-to-noise ratio, and entropy evaluation parameters. The calculation method of the mean parameter is shown in Eq. (12).

$$\mu = \frac{\sum_{c=1}^{C}\sum_{d=1}^{D} F(x_c, y_d)}{z} \tag{12}$$

In Eq. (12), x_c and y_d represent the pixel values of the image at points c and d respectively, C represents the total number of pixels in the image in the X-direction, and D represents the total number of pixels in the image on the Y-axis. z represents the total amount of pixels in the image, and the calculation method for the average gradient is shown in Eq. (13).

$$G = \frac{1}{(M-1)(N-1)}\sum_{c=1}^{M-1}\sum_{d=1}^{N-1}\sqrt{\frac{((\frac{\partial F(x_c,y_d)}{\partial x_c})+(\frac{\partial F(x_c,y_d)}{\partial y_d}))}{2}} \tag{13}$$

In Eq. (13), M and N denote the width and height of the image respectively. The calculation method of standard deviation is denoted in Eq. (14).

$$S = \sqrt{\sum_{c=0}^{M-1}\sum_{d=0}^{N-1}\frac{(F(c,d)-\mu)^2}{z}} \tag{14}$$

The above parameters are compared to judge the quality of IF. If it meets the requirements, it will output it. If it does not meet the requirements, it will return it to the image feature extraction module to extract and fuse the image features again until it meets the requirements. Through this system, the clarity of medical IF can be significantly improved, thereby improving the accuracy of medical diagnosis.

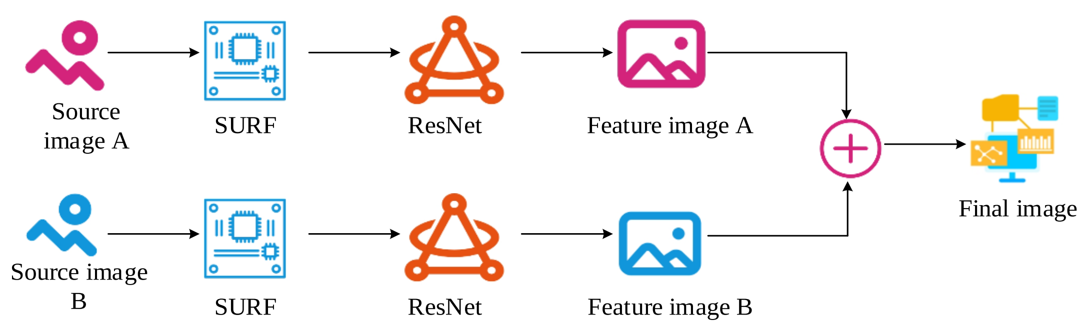


Fig. 5. Image feature extraction fusion structure diagram.

IV. Results

A. *Performance Analysis of SURF-ResNet Algorithm*

To identify the superiority of SURF-ResNeT algorithm, this study conducted comparative experiments on High Pass Filter (HPF) HPF-CNN algorithm, Principal Component Analysis (PCA) PCA-CNN algorithm, and Particle Swarm Optimization (PSO) algorithm. The experiment environment configuration is indicated in Table I.

TABLE I EXPERIMENTAL ENVIRONMENTAL CONFIGURATION

Experimental Environment	Index	Allocation
hardware environment	OS	Windows 10
	CT type	EBCT
	CPU type	Intel i7
	Memory size	64GB
software environment	Operating platform	Matlab
		VC++6.0

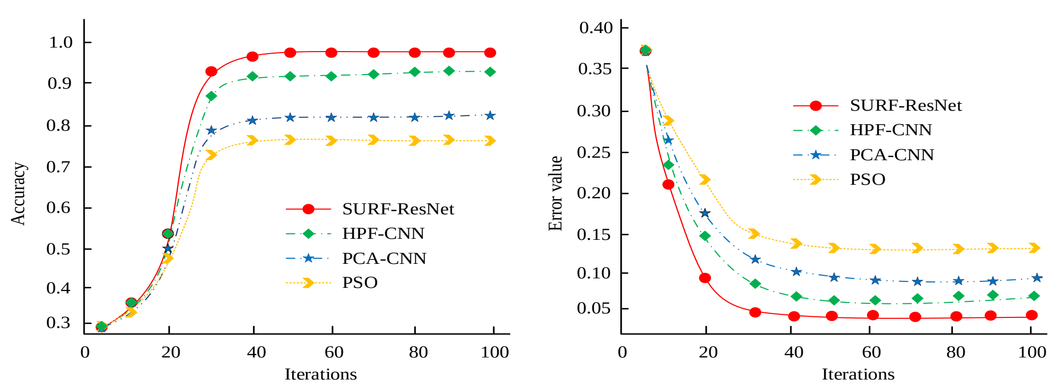
The dataset used in the experiment was from Harvard Medical School in the United States. Firstly, this dataset was utilized to analyze various parameters of the algorithm during the experiment, to select appropriate parameters for the experiment. The analysis results are shown in Table II.

According to Table II, when the threshold of SURF algorithm was 500, the maximum PL of residual network algorithm was 3, and the residual dense fast growth rate was 64, the performance of this algorithm was optimal. When the cut-off frequency of the filter in the HPF algorithm was set to 60% and the order of the filter was 40, the performance of the HPF algorithm reached its optimum. The dimension dim was set to 3 and the particle swarm size was set to 150 in the PSO algorithm; when setting the learning rate to 0.1 and the sample size batch to 50 in the CNN algorithm, the performance of both algorithms was the best. So this study conducted comparative experiments using the above experimental parameter configuration, experimental dataset, and experimental environment. The comparison results of the accuracy and error rates of the algorithms are shown in Fig. 6.

From Fig. 6(a), the accuracy of SURF-ResNet algorithm, HPF-CNN algorithm, PCA-CNN algorithm, and PSO algorithm reached their maximum at 30 iterations, with accuracy values of 0.98, 0.89, 0.76, and 0.72, respectively. From the above data, SURF-ResNet had the highest accuracy. From Fig. 6(b), the error values of the four algorithms decreased with the increase of iteration times. Among them, the error value of the SURF-ResNet algorithm dropped to a minimum of 0.03 at 40 iterations and remained stable thereafter. The error values of the other three algorithms also reached their lowest point at 40 iterations, with error values of 0.07, 0.12, and 0.14, respectively. Subsequently, comparative experiments were conducted on the loss function values of the four algorithms and the time taken to extract image features. The experiment findings are denoted in Fig. 7.

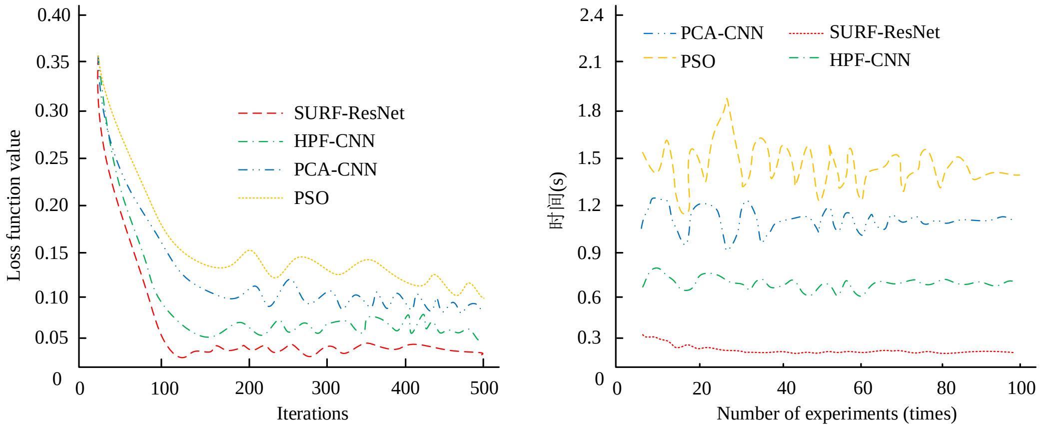
TABLE II ANALYSIS OF ALGORITHM PARAMETERS

Algorithm	Parameter	Size	Accuracy	Algorithm	Parameter	Size	Accuracy
SURF	Threshold	450	89.6%	HPF	Order	35	86.8%
		500	97.6%			40	96.2%
		550	92.1			45	90.7%
	Pooling layer	2	90.6%	PSO	Dim	2	90.2%
		3	96.5%			3	96.9%
		4	91.3%			4	91.6%
	Growth rate	62	87.9%		Particle swarm size	140	90.2%
		64	95.8%			150	97.9%
		66	90.4%			160	87.9%
HPF	Cut-off frequency	55%	90.7%	CNN	Learning Rate	0.05	90.7%
		60%	97.8%			0.1	97.4%
		65%	87.7%			0.15	89.1%



(a) Comparison of Accuracy of Four Algorithms (b) Comparison of error values for four algorithms

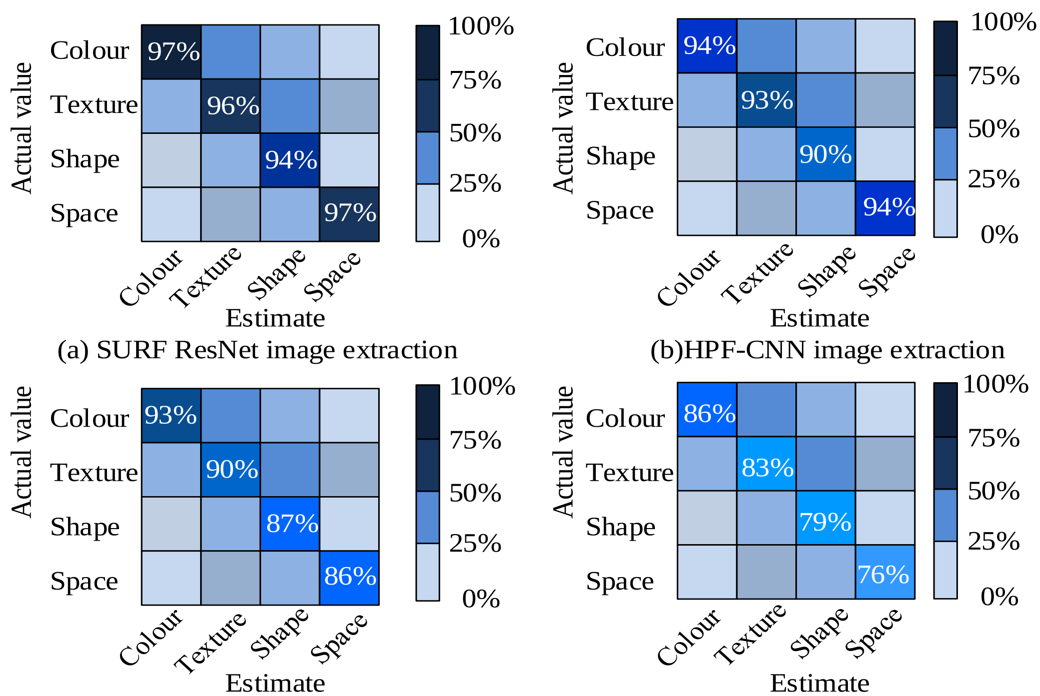
Fig. 6. Algorithm accuracy and error values.



(a) Comparison of loss functions for four algorithms (b) Comparison of computation time for four algorithm

Fig. 7. Algorithm loss function and time comparison.

According to Fig. 7(a), the loss function values of SURF-ResNet algorithm, HPF-CNN algorithm, PCA-CNN algorithm, and PSO algorithm all sharply decreased when the number of iterations reached 100. Among them, the loss function values of SURF-ResNet algorithm fluctuated between 0.01 and 0.03 afterwards. The loss function value of the HPF-CNN algorithm fluctuated between 0.05 and 0.09. The loss function value of PCA-CNN algorithm fluctuated between 0.10 and 0.12 after reaching 100 iterations, while the fluctuation range of PSO algorithm was 0.12 and 0.16, and the stability of the loss function value of this algorithm was the worst. From Fig. 7(b), the average time for image feature extraction using SURF-ResNet algorithm was 0.12s, and the extraction time of this algorithm was almost stable. The average feature extraction time of HPF-CNN and PCA-CNN algorithms was 0.7 and 1.0 seconds, respectively. It can be seen from the scatter plot that the extraction time of this algorithm was unstable. The average feature extraction time of PSO algorithm was 1.5 seconds, and the extraction time of this algorithm was extremely unstable. Finally, a comparative experiment was conducted on the ability of four algorithms to extract image features, and the color, texture, shape, and spatial information of the extracted images were compared. The experimental results are shown in Fig. 8.



(a) SURF ResNet image extraction (b)HPF-CNN image extraction

(c)PCA-CNN image extraction (d)PSO image extraction

Fig. 8. Image extraction capability.

Fig. 8 shows the indicators of the ability to extract image feature information using four confusion matrix algorithms. The elements on the main diagonal of the confusion matrix denote the proportion of correctly extracted samples, the elements in the lower left triangle represent the proportion of missed image information features, and the elements in the upper right triangle represent the proportion of false detected image information features. From Fig. 8, the SURF-ResNet algorithm had an accuracy rate of 97%, 96%, 94%, and 97% for feature extraction in terms of image color, texture, shape, and space. The HPF-CNN algorithm had a feature extraction accuracy of 94%, 93%, 90%, and 94% in these four aspects of images, respectively, and its feature extraction ability was lower than the algorithm raised in the study. The accuracy rates of the PCA-CNN algorithm were 93%, 90%, 87%, and 86%, respectively. The PSO algorithm had the lowest image feature extraction ability, with extraction accuracy rates of 86%, 83%, 79%, and 76% in image color, texture, shape, and space, respectively. From the above experiment outcomes analysis, the SURF-ResNet algorithm proposed in this study has the highest accuracy in image feature extraction, the fastest extraction speed, the strongest feature extraction ability, and a much higher comprehensive ability than other comparative algorithms.

B. Analysis of Application Effectiveness of SURF-ResNet Algorithm in Medical Image Fusion System

The optimized ResNet deep learning algorithm was applied to the medical IF system, and the IF effect of the system was analyzed through simulation experiments. The accuracy and clarity of the medical IF system based on SURF-ResNet algorithm, HPF-CNN algorithm, PCA-CNN algorithm, and PSO algorithm were analyzed. The experimental results are shown in Fig. 9.

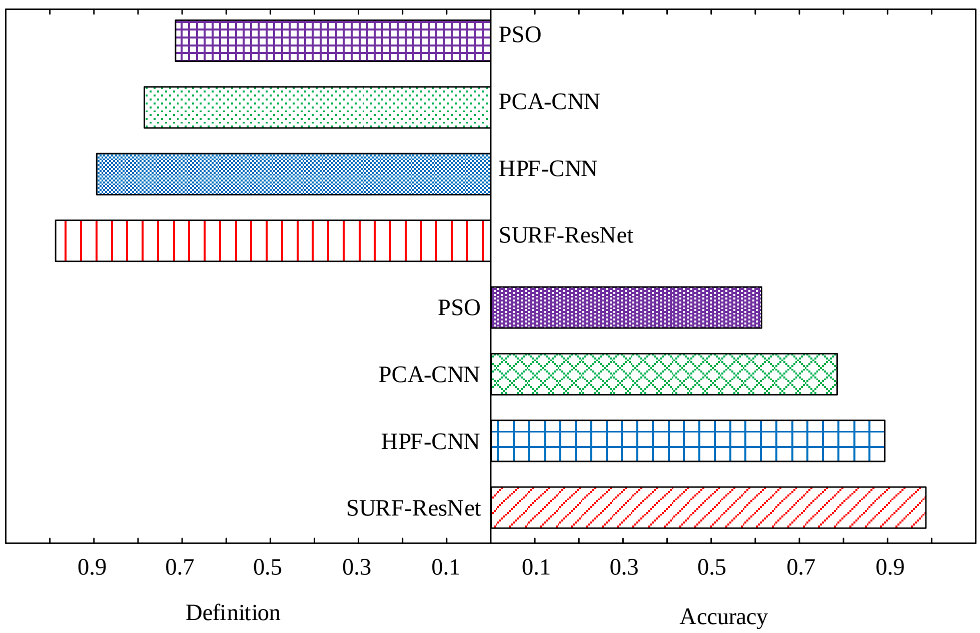


Fig. 9. Comparison of accuracy and clarity.

The upper left part of Fig. 9 represents the IF clarity of four IF systems, and the lower right part represents the IF accuracy of the four IF systems. From this figure, the IF system based on SURF-ResNet algorithm had the highest clarity after IF, reaching 0.97. The clarity of the IF system based on HPF-CNN algorithm was 0.89, the clarity of the IF system based on PCA-CNN algorithm was 0.84, and the clarity of the IF system based on PSO algorithm was the lowest, 0.76. The accuracy of IF in the four systems was 0.98, 0.91, 0.82, and 0.69, respectively. The SURF-ResNet system had the highest accuracy and the PSO system had the lowest accuracy. Afterwards, the Mutual Information (MI), Information Entropy (IE), Structural Similarity (SSIM), Spatial Frequency (SF), Average Gradients (AG), and Correlation Coefficient (CC) of the fused system images were evaluated. The evaluation results are shown in Table III.

TABLE III COMPARISON OF VARIOUS INDICATORS

Image Fusion System	SURF-ResNet	HPF-CNN	PCA-CNN	PSO
MI	3.2	2.4	1.7	0.9
IE	2.9	2.1	1.8	0.8
SSIM	0.59	0.56	0.43	0.38
SF	13	9	7	6
AG	28	26	19	15
CC	5.6	4.5	2.8	2.6

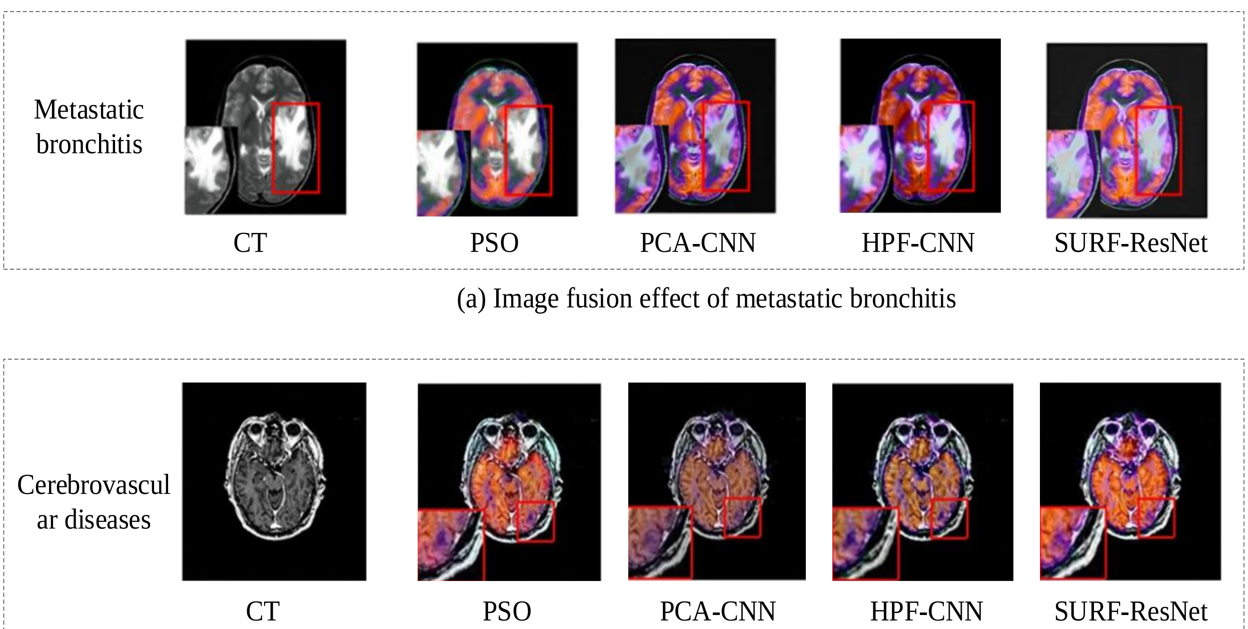
From Table III, among the four systems fuse various indicators of the image, the MI and IE indicators represent the feature information transferred from the source image to the fused image and the amount of information contained in the fused image. The higher the MI and IE values, the more feature information extracted from the fused image. According to Fig. 10(a), among the four IF systems, the average MI of SURF-ResNet was the highest at 3.2, while the average MI of HPF-CNN, PCA-CNN, and PSO were 2.4, 1.7, and 0.9, respectively. In Fig. 10(b), the IE value of the image obtained by the SURF-ResNet IF system was much higher than that of other comparison systems, with an average IE value of 2.9. The SSIM index is composed of the correlation loss, brightness, and contrast distortion of the image, used to reflect the SSIM between the fused image and the source image. The larger the value of this index, the smaller the information loss and distortion during the IF process. According to Fig. 10(c), the SSIM values of SURF-ResNet, HPF-CNN, PCA-CNN, and PSO IF systems were 0.59, 0.56, 0.43, and 0.38, respectively. The SF and AG values represent the gradient information of the fused image, with higher AG and SF values indicating richer edge and texture details of the fused image. From Fig. 10(d) and 10(e), the SURF-ResNet IF system had the highest AG and SF values of 13 and 28, respectively, among the four IF systems. The AG and SF values of HPF-CNN, PCA-CNN, and PSO IF systems were 9, 26, 7, 19, and 6, 15, respectively. The CC value represents the degree of linear correlation between the fused image and the source image, and the higher the value, the more similar the fused image is to the source image. As shown in Fig. 10(f), the CC value of the SUDF-ResNet fusion image was the highest average of the four fusion images, with a value of 5.6. Furthermore, the medical IF system was applied in practical applications to compare CT fusion images of metastatic bronchitis and cerebrovascular diseases. The results are shown in Fig. 10.

Fig. 10 shows the presentation effect of CT fusion images for two different diseases. Fig. 10(a) shows the fusion image of metastatic bronchitis. From Fig. 10, the PSO IF system had insufficient clarity in the fusion image, while the PCA-CNN system had severe edge brightness distortion in the fusion image, while the HPF-CNN system had severe color distortion in the fusion image. Only the SURF-ResNet system had good color preservation, clear edges, high detail quality, and high quality in the fusion image. Further comparison was made between the medical IF technology based on the SURF-ResNet algorithm and the widely used Alpha fusion technology, Early Fusion (EF), and Gaussian Pyramid Fusion (GPY). The results are shown in Table IV.

According to Table IV, the medical IF technology based on the SURF-ResNet algorithm proposed in the study was compared with other IF technologies. After fusing the images, the SURF-ResNet fusion technology significantly outperformed other fusion technologies in terms of image performance. From the above experiment findings, deep learning algorithm systems based on image features and ResNets can improve the clarity of fused images and preserve image information to the greatest extent in medical IF systems.

TABLE IV PERFORMANCE ANALYSIS OF IMAGE FUSION TECHNOLOGY

Method	Image clarity	Distortion	Detail quality	Color quality
SURF-ResNet	98.6%	0.9%	97.5%	96.8%
Alpha	92.4%	1.4%	89.7%	90.7%
EF	89.6%	2.1%	82.1%	86.5%
APY	83.8%	2.9%	78.3%	80.7%



(a) Image fusion effect of metastatic bronchitis

(b) Image fusion effect of cerebrovascular diseases

Fig. 10. Simulation experimental results.

V. Discussion

This study conducted experimental analysis on the performance of deep learning algorithms in medical IF systems, and analyzed the role of deep learning algorithms in the system. Firstly, SURF-ResNet deep learning algorithm was experimentally compared with HPF-CNN, PCCA-CNN, and PSO algorithms. The outcomes indicated that the maximum accuracy values of the four algorithms were 0.98, 0.89, 0.76, and 0.72, respectively. The minimum error values were 0.03, 0.07, 0.12, and 0.14, respectively, which are similar to the experiment outcomes of Li et al. [20]. This indicated that the SURF-ResNet deep learning algorithm has the highest accuracy in extracting data features. The reason for this may be because the SURF-ResNet algorithm first performs an initial filtering of the image information using the SURF algorithm, which increases the accuracy of the algorithm. The experiment outcomes also showed that the mean time used by the four algorithms for image feature extraction was 0.12s, 0.6s, 1.0s, and 1.5s, respectively. The SURF-ResNet deep learning algorithm had the shortest usage time. Further comparative experiments were conducted on four algorithms for extracting color, texture, shape, and spatial information from images. The experiment outcomes showed that the SURF-ResNet algorithm had the highest accuracy in feature extraction of image color, texture, shape, and space, with 97%, 96%, 94%, and 97%, respectively. The experiment outcomes coincide with the research findings of Elazab's team [21]. The reason for this phenomenon is that the combined use of the SURF algorithm and the ResNet algorithm, where the image information is extracted and computed again, improves the algorithm's ability to extract image features. This demonstrates the significant advantages of SURF-ResNet deep learning algorithm in image feature extraction. The role of deep learning algorithms were simulated and analyzed in medical IF systems. The experiment outcomes showed that among the medical IF systems based on the four algorithms, the SURF-ResNet medical IF system had the highest accuracy and clarity of fused images, with 0.98 and 0.97 respectively. The accuracy and clarity of fused images in the HPF-CNN system were 0.91 and 0.89, respectively. The accuracy and clarity of the PCA-CNN system for fusing images were 0.82 and 0.84, respectively. The accuracy and clarity of PSO system fusion images were the lowest at 0.69 and 0.76, respectively. Afterwards, comparative experiments were conducted on various indicators of fused images of the four systems. The experimental results showed that the various indicators of medical fused images of SURF-ResNet system were the highest among several IF systems. The MI, IE, SSIM, SF, AG, and CC values of the system were 3.2, 2.9, 0.59, 13, 28, and 5.6, respectively, which are consistent with the experimental results of Khan et al. [22]. The reason for this result may be that the residual learning block in ResNet deep learning algorithm can accurately extract feature information from medical images, while there are still some errors in the image feature extraction ability of CNN algorithm and PSO algorithm. The SURF-ResNet deep learning algorithm significantly improved the accuracy and clarity of IF in medical IF systems. The fusion accuracy, similarity, and correlation of medical fusion images in the SURF-ResNet system were superior to other systems. Afterwards, a comparative experiment was conducted on the IF effects of two different diseases. The experimental results showed that the SURF-ResNet system fused images with better color, detail, and edge clarity than other systems. This result coincide with the research findings of Deng et al. [23]. The results show that the proposed SURF-ResNet algorithm can effectively extract image features and improve the accuracy of image extraction by using the two-feature extraction method in the medical IF process. The above experimental results indicate that using SURF-ResNet deep learning algorithm in medical IF systems can raise the clarity and accuracy of fused images, thereby improving the accuracy of medical diagnosis.

VI. Conclusion

To solve the problem of high blurring and low accuracy of medical fusion images in medical diagnosis, this study combined ResNet algorithm with SURF algorithm and proposed SURF-ResNet algorithm, based on which SURF-ResNet medical IF system was proposed. The study conducted comparative experiments of SURF-ResNEet algorithm, HPF-CNN algorithm, PCA-CNN algorithm and PSO algorithm. The experimental results showed that the SURF-ResNet algorithm outperformed the comparison algorithms in terms of accuracy, error value and image information extraction time performance. Afterwards, the medical IF system based on the four algorithms was analyzed in simulation experiments, and the experimental results showed that the accuracy and the clarity of the fused images of the medical IF system based on the SURF-ResNet algorithm were better than the other systems. The above results indicated that the proposed medical IF system based on SURF-ResNet deep learning algorithm had the highest fusion image accuracy and clarity, the fastest IF speed, and the best overall performance. The medical fusion images obtained by this method have detailed patient information, which can better assist doctors in determining the patient's condition. In the future, the results of medical IF can be used to carry out personalized medical treatment and disease prevention by virtue of the patient's radiotherapy measurement. However, nowadays, medical image data come from different devices, and the format and standard of medical images are inconsistent, which brings difficulties for data processing and analysis. The ResNet algorithm in the fusion algorithm is prone to gradient vanishing or exploding during the training process, which can have a negative impact on the experimental results. In the future, it can be optimized by introducing batch normalization or other artificial intelligence technologies.

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