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ResNet and its application to medical image processing: Research progress and challenges

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ABSTRACT

Background and objective: Deep learning, a novel approach and subset of machine learning, has drawn a growing amount of attention from computer vision researchers in recent years. This method has drawn a lot of interest because of its extraordinary ability to interpret medical pictures, especially when combined with residual neural networks, which have helped to progress the field.
Methods: In this paper, the following research is carried out on the residual network. First, the research status of ResNet in the medical field is introduced. The fundamental idea behind the residual neural network is then explained, along with the residual unit, its many structures, and the network architecture. Second, four aspects of the widespread use of residual neural networks in medical image processing are discussed: lung tumor, diagnosis of skin diseases, diagnosis of breast diseases, and diagnosis of diseases of the brain. Finally, the main issues and ResNet's future development in the area of processing medical images are discussed.
Results: In the area of medical graph processing, residual neural networks have made strides and have had success in the clinical auxiliary diagnosis of serious illnesses such as lung tumors, breast cancer, skin conditions, and cardiovascular and cerebrovascular diseases.
Conclusion: We thoroughly sorted out the most recent developments in residual neural network research and their use in medical image processing, which serves as a crucial point of reference for this field of study. It offers a helpful reference for further promoting the application and research of the ResNet model in the field of medical image processing by summarising the application status and issues of the ResNet model in the field of medical image processing and putting forwards some future development directions.

1. Introduction

Medical images play an important role in clinical disease prediction, classification, and treatment [1]. Currently, the primary method for clinical imaging diagnosis is still the traditional manual reading, which is unable to keep up with the ever-growing volume of imaging data. Additionally, when faced with numerous similar images, relying on naked-eye judgments can lead to biases and erroneous conclusions. However, with the rapid advancement of internet technology and medicine, deep learning (DL) has garnered increasing attention and has found broad applications in computer vision, speech processing, big data analysis, and other fields. DL is becoming more and more important in the medical profession as a crucial tool for image-based auxiliary diagnosis technology, considerably improving both the efficiency and accuracy of diagnosis.

In recent years, residual neural networks (ResNet) and their optimization are one of the hotspots in deep learning research and are widely used in the field of medical images. Clinical diagnosis, staging, metastatic evaluation, therapy planning, and target selection for serious illnesses including tumors, cardiovascular and cerebrovascular ailments, as well as nervous system disorders, have made significant strides. Liu et al. [2] used a multi-scale residual neural network (MSResNet) to collect multi-scale information from convolution kernel images of different sizes and carried out residual learning on the neural network. This method implements multi-scale feature learning. Compared with the traditional deep convolutional network, the classification effect is better. Maier et al. [3] believe that a residual neural network is a network that has an important impact on the field of medical images.

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The success of a residual neural network is inseparable from the optimal learning algorithm of the network.

ResNet-22, a deep convolutional neural network created exclusively for breast cancer screening categorization, was proposed by Wu et al. in their study [4]. Their model, which is based on the common ResNet architecture, has a depth-to-width ratio that is optimized for the analysis of high-resolution medical pictures. Experimental findings show how successful their strategy is. The findings of Karthik et al.'s [5] use of residual neural networks to identify COVID-19 in chest X-ray pictures demonstrate the efficiency of the technique. Based on ResNet and UNet++, Lu et al. suggested the WBC-Net deep learning network. Their approach comprises a hybrid skip route that makes use of dense convolutional blocks to collect and merge picture data of various scales, as well as a context-aware feature encoder that uses residual blocks to extract multi-scale features. With this method, white blood cell image segmentation accuracy is increased. Additionally, Nazir et al. [6] introduced the OFF-eNET architecture for automatic intracranial vessel segmentation, which combines residual mapping and Inception modules. A richer visual representation is achieved, and computational efficiency is improved. The results show that in-depth research on residual neural networks is of great significance.

Deep learning has shown its unique advantages in search technology, data mining, machine learning, machine translation, natural language processing, multimedia learning and so on. ResNet has advantages for processing medical pictures since it can extract and categorize intricate elements from these images, enhancing their accuracy and resilience. Additionally, ResNet is highly effective in a variety of medical image processing jobs due to its depth and accuracy. In contrast to previous neural network models used in medical image processing, ResNet can quickly train very deep neural network models and, by linking across layers, can prevent the gradient disappearance problem. As a result, ResNet performs better at digesting the intricate details of medical photos.

2. Residual neural networks

2.1. Residual units

The combination of deep learning and residual neural networks has significantly contributed to advancements in medical image processing. Deep learning techniques, including ResNet, have shown remarkable ability in extracting meaningful features from medical images, enabling accurate and efficient diagnosis of various diseases. The residual unit is the fundamental building component of a residual network. The residual unit is composed of a stack of convolutional Conv layers, batch normalized BN layers, and non-linear activation function ReLU layers. ResNet's architecture and skip connections have particularly helped address the challenges of training deep networks, improving the interpretability and performance of medical image analysis. Fig. 1 is a schematic illustration of a residual unit. Let x be the first residual unit's input. The result of this algorithm may then be formalized to conduct the following mathematical computation.

$$x_{l+1} = f(x_l + F(x_l, W_l)) \tag{1}$$

The function $F(x_l, W_l)$ represents the residual function, where W_l denotes the weight parameter associated with it. Additionally, f (•) denotes the nonlinear activation function, specifically the Rectified Linear Unit (ReLU). Both x_l and $F(xl, Wl)$ must have identical dimensions; however, if there is a difference in dimensions, such as when changing input/output channels, a shortcut connection applies a linear mapping w_s to match the dimensions of the two.

$$x_{l+1} = f(W, x_l + F(x_l, W_l)) \tag{2}$$

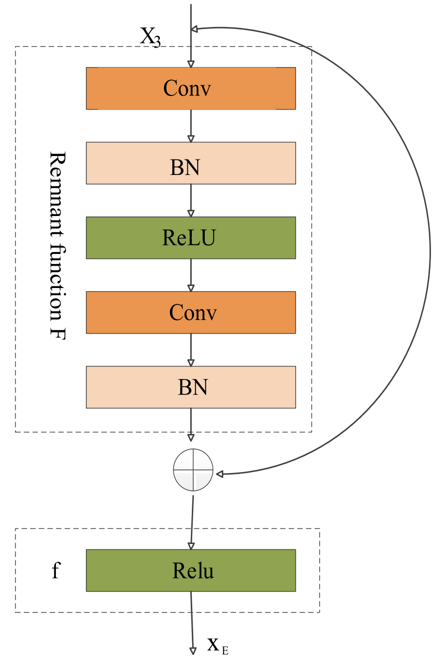

Fig. 1. Residual unit.

The residual function F has a flexible and changeable shape. Three convolutional layers can be layered in addition to two convolutional layers.

By stacking many residual learning units, a deep residual network is constructed. The convolutional layer Conv, the nonlinear activation function layer ReLu, and the batch normalization layer BN are the layers that the deep residual network the delivers the input image data in that sequence. The results after processing are then sent through several residual units, the batch normalization layer BN, and several fully linked layers. Obtain the output result last.

When building ultra-deep networks such as networks with more than 100 layers. The straight stacking of numerous original residual learning modules will result in a parameter explosion. He et al. [7] introduced a residual module structure termed "bottleneck" to minimize the number of parameters of the deep network without sacrificing accuracy, as illustrated in Fig. 2. This bottleneck structure's main design objective is to reduce the number of parameters and corresponding calculation to quicken the deep residual network's training process.

2.2. Different ways of constructing residual units

Researchers have explored various placements and combinations of batch normalization [8] and the activation function Relu based on the original residual unit. A residual network's network structure is a deep neural network made up of several residual units, each of which can be either a basic residual unit or a bottleneck residual unit. A residual network's input layer is often a convolutional layer, and its output layer is typically a global average pooling layer and a softmax layer. Each residual unit in a residual network has two outputs: one computed by the residual connection and the other passed directly from the input via a Shortcut Connection. These two attributes are added together and fed to the next layer. It is discovered that the various residual unit creation approaches affect network correctness, convergence, and training speed. In 2016, He et al. [9] presented the residual unit of pre-activation, which increases the model's generalization capacity and lowers the effect of overfitting. Han et al. [10] conducted more

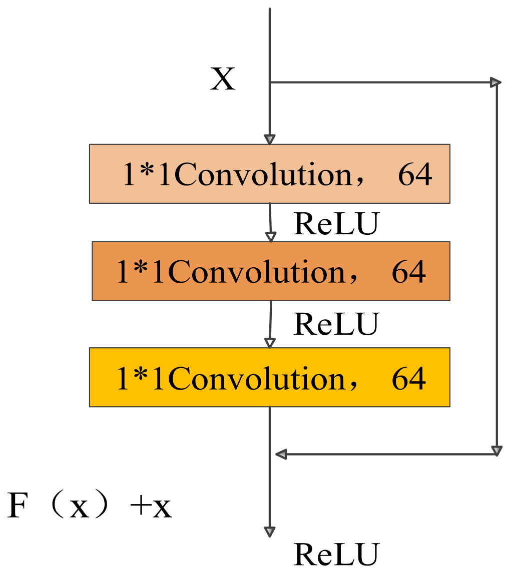

Fig. 2. Bottleneck structure.

experiments on the residual unit on this premise, and the structural diagram of several residual units is shown in Fig. 3.

2.3. Different ways of constructing network frameworks

Despite its initial success, the original architecture of the residual network still exhibits notable limitations, particularly when it comes to convergence in very deep networks [11,12]. To address these challenges and improve the network's learning capacity while making it easier to optimize, researchers have proposed various modifications to the residual network architecture. Some of these enhanced frameworks will be discussed below.

2.3.1. Deep pyramid residual networks

According to Veit et al. [13], residual networks may be viewed as a collection of shallow networks. They demonstrated that removing a single residual unit from the network, which corresponds to discarding only one shortcut connection, has little impact on the network's overall performance. This suggests that eliminating residual units is equivalent to removing some shallow networks from the ensemble. In contrast, removing any layer from an ordinary network, such as VGG network, can result in severe performance degradation. Although removing the building blocks with downsampling functions in residual units causes the feature map's dimension to double, which increases classification error, removing those blocks does not adversely affect the network's performance when training residual networks with random depths [14]. Subsequently, Han et al. [15] introduced the PyramidNet, a deep residual network with a pyramid-like structure shown in Fig. 4. In this network, the width gradually increases with depth, resembling a pyramid whose base widens from top to bottom.

With a downsampling function, the number of feature map channels is gradually increased rather than suddenly increased in each residual unit. Additionally, when feature map size grows, the created network design combines residual and conventional networks by using zero-padding identity map shortcut connections, as seen in Fig. 5. Because there are no extra parameters, this design does not create overfitting. Surprisingly, it has exceptional generalization ability when compared to other shortcuts. Using downsampling to remove leftover units does not impact performance in the new network design.

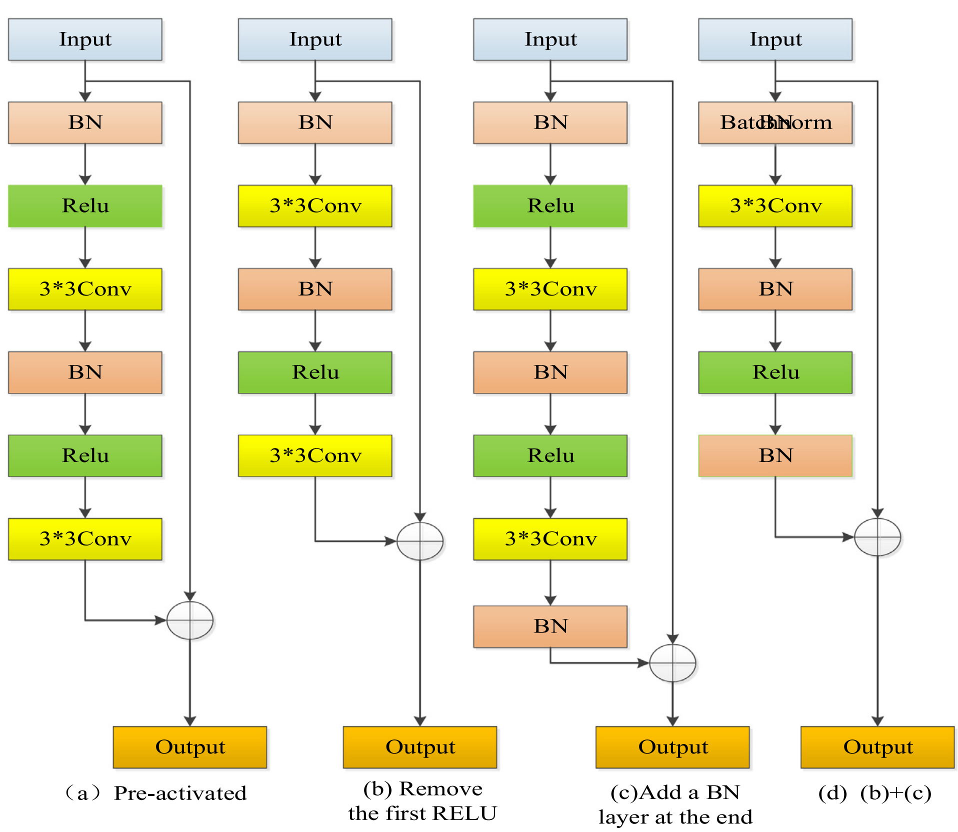

Fig. 3. Structure diagram of different residual units.

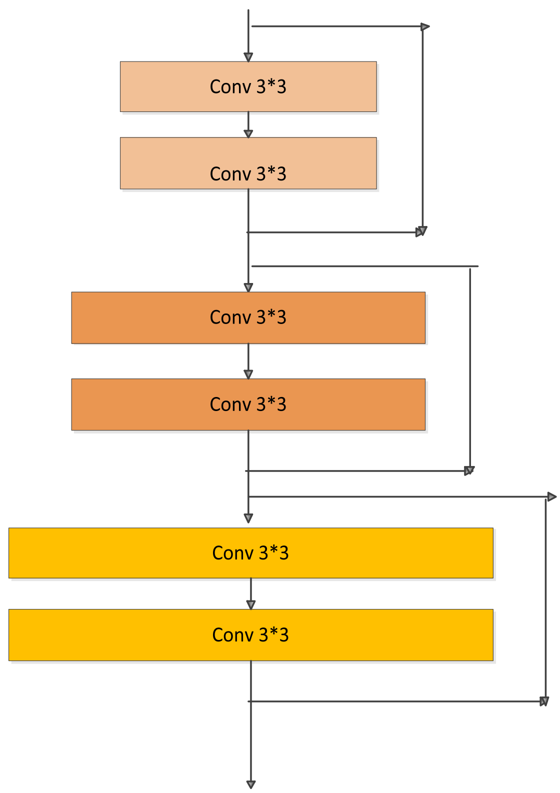

Fig. 4. Deep pyramidal residual unit.

2.3.2. Dense Network

Implements a dense convolutional network (DenseNet) in which each layer may directly get the output of all preceding layers [16]. The new network design tackles the issue of gradient disappearance, improves feature reuse, and drastically decreases the number of parameters. In this design, the input to each layer consists of feature maps from all previous levels, and its output is supplied to all following layers. This technique enables excellent information flow across all network tiers, allowing for greater gradient propagation and feature reuse while reducing the number of parameters required to attain high performance.

The outputs of the identity maps are added together in the original deep residual network. In this situation, if the distribution of feature mappings across the two layers is extremely varied, it may influence feature reuse and impede information flow propagation. The dense network is shown in Fig. 6. By cascading feature maps instead of adding them directly, we can increase the diversity of the output while preserving all feature maps, facilitating feature reuse. Experiments show that the dense network has higher parameter efficiency and better convergence effect under the same parameter amount.

2.3.3. Deep attention residual networks

Attention mechanisms also play an important role in computer vision. The attention mechanism [15,17] can not only make the operation focus on a specific area but also enhance the feature importance of this part of the area. Wang et al. [18] presented the Residual Attention Network (RAN) to incorporate an attention mechanism in deep residual networks. An attention residual unit, shown in Fig. 7, is divided into two branches. The branch on the right is an ordinary convolutional network, and the trunk branch, is called

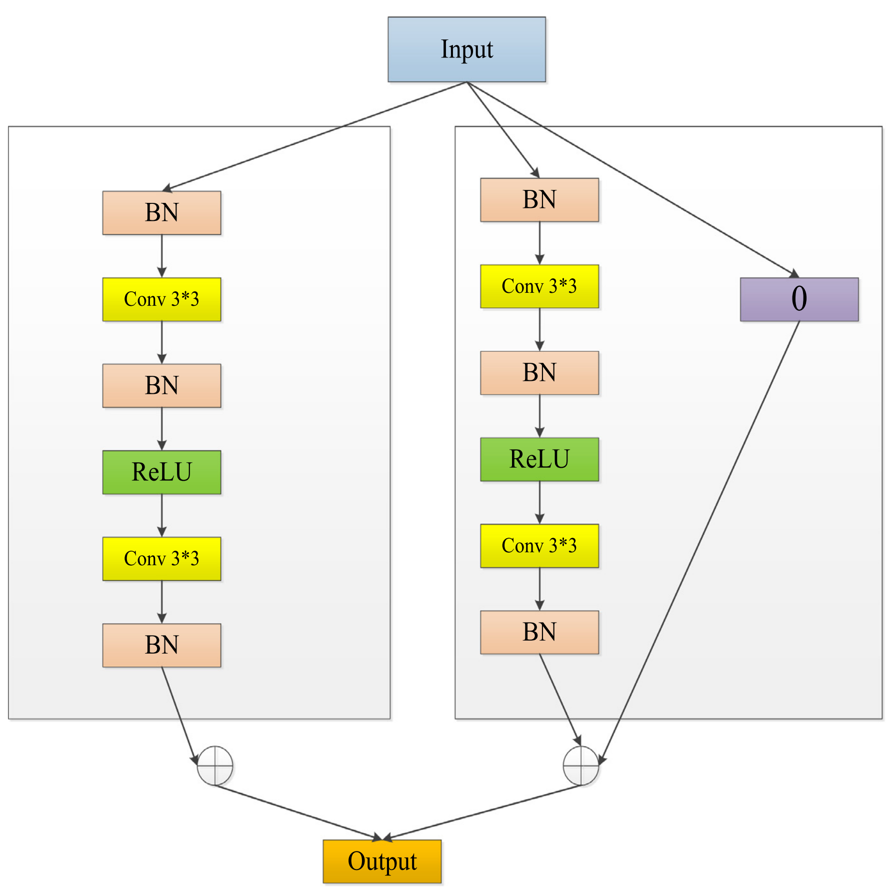

Fig. 5. Residual unit with aero-padded identity mapping shortcut.

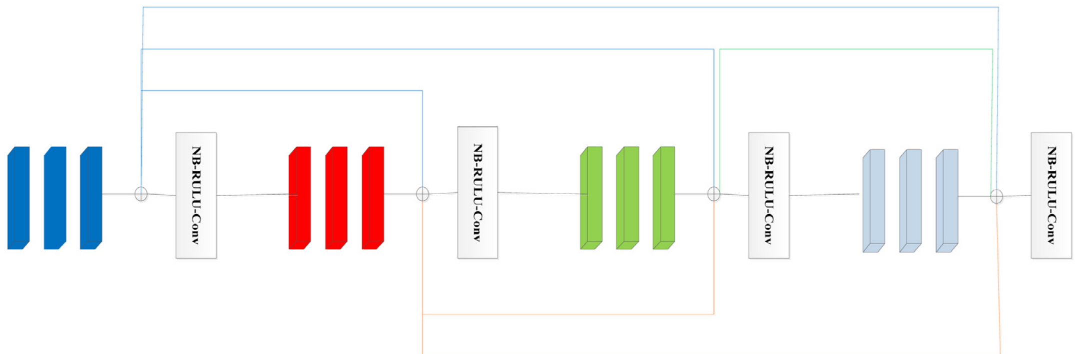

Fig. 6. Residual dense network.

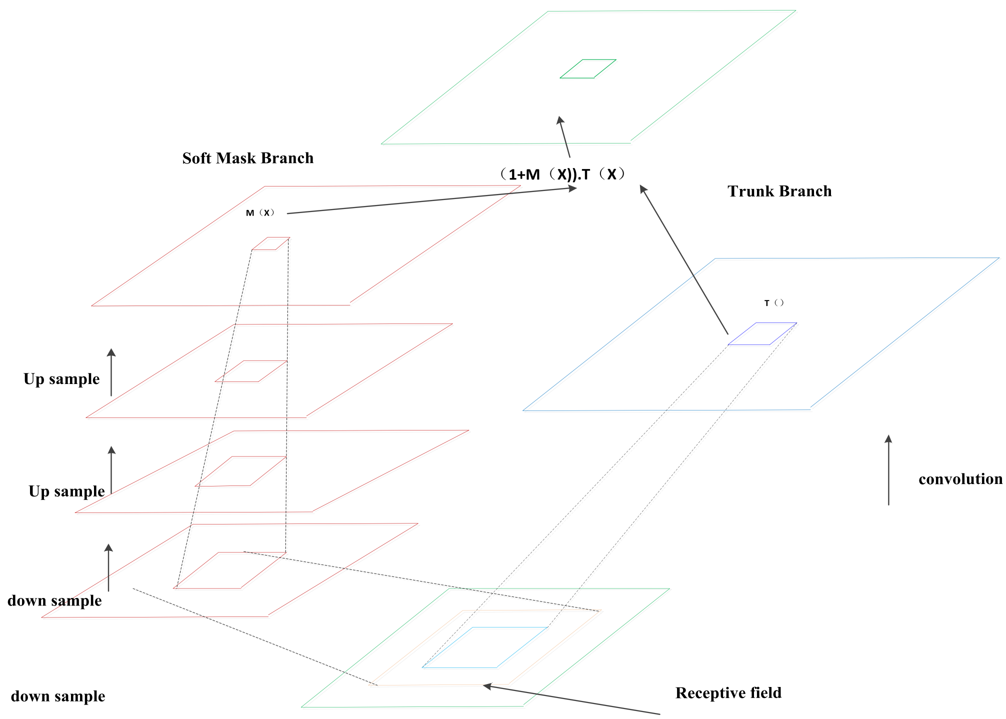

Fig. 7. Attention Residual Unit Structure Diagram.

the Trunk Branch. The branch on the left is to get a mask, the function of which is to get the attention map of the input feature x, so it is called Mask Branch. This Mask Branch contains the downsampling and upsampling processes, whose goal is to ensure that the output size of the right branch is the same. The residual attention paradigm not only improves network performance but also provides high scalability. It can be used with the majority of today's deep networks to enable end-to-end training. The network may also be readily expanded to hundreds of layers due to its residual nature.

2.3.4. 3D ResNet U-Net

3D U-Net [19] is an easy adaptation of U-Net for 3D image segmentation. In comparison to U-Net, the network uses just three downsampling operations and batch normalization after each convolutional layer; nevertheless, neither 3D U-Net nor U-Net uses dropout. In the 2018 MICCAI Brain Tumour Segmentation Challenge (brats), a team from the German Cancer Research Centre used 3D U-Net [4]. Only a few tweaks were required to place second in the challenge. In comparison to many current networks, the 3D U-Net is still thought to be fairly helpful [20,21]. Yu Wei [22] proposed combining the 3D U-Net network with the residual network's residual blocks to create a new 3D residual U-Net network. Fig. 8 displays its structure. A residual module will be used to replace the second convolution operation of each layer in the 3D residual U-Net network. When the segmentation result is finally obtained, the multi-scale feature information from the last three segmentation layers is fused to optimize the segmentation effect. The size of the convolution kernel utilized in all convolution layers in the 3D residual U-Net network structure is 3*3*3, and the residual module has three convolution operations, allowing the residual block's receptive field to be enlarged. By introducing the residual block structure into the 3D U-Net network, the vessel region's feature information may be preserved in the network as much as possible, hence improving network segmentation performance.

3. Residual neural network improvement mechanism

The original residual network topology still has significant flaws, and it is difficult to converge on very deep networks. Data imbalance, improper labeling, noise interference, and variable

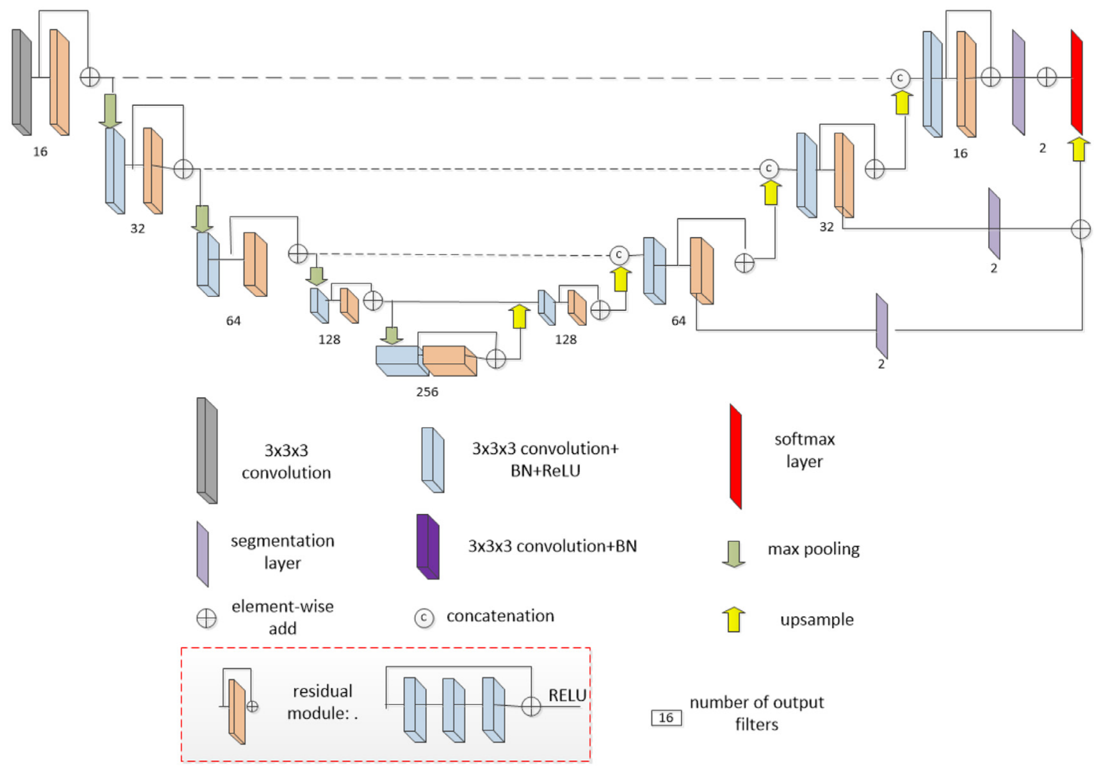

Fig. 8. 3D Residual U-Net structure.

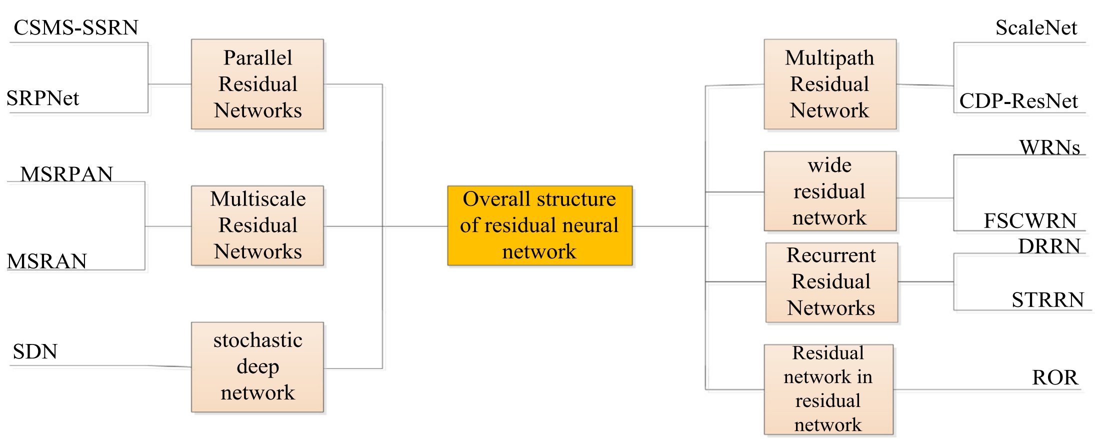

Fig. 9. The overall structure of the residual neural network.

sample size are the primary issues ResNet faces in the realm of analyzing medical images. The model's performance may be impacted by these issues, which might result in the model's inability to generalize well and overfitting or underfitting. Optimizing the residual neural network [23] and improving the entire network structure, can effectively reduce overfitting and improve the network learning ability. Finally, which occupies a prominent role in the field of deep learning, shines in image processing but also offers a wide variety of applications in other domains including speech recognition and natural language processing. This study summarises the overall network structure from seven viewpoints: the parallel residual network, the multi-scale residual network, the random deep network, the multi-path residual network, the wide residual network, the recursive residual network, and the residual network inside the residual network. The fundamental model may be seen in Fig. 9.

3.1. Parallel Residual Networks

Improve network accuracy and minimize network computation by fully extracting picture information via numerous concurrent branches. Using 3-dimensional channels and spatial attention, Lu et al. [24] created a multi-scale spatial-spectral residual network to fully extract the properties of high-resolution images and boost classification accuracy. The three-branch architecture is made up of three stages of independent and parallel residual blocks (CSMS-SSRN). Using various 3D convolution kernels, the spectral and spatial properties are continually learned from the relevant residual blocks. To extract spectral features utilizing parallel branches with the same structure and shared parameters to decrease trainable parameters and optimize computation, Zhang et al. [25] proposed spatial residual blocks combined with parallel networks (SRPNet).

3.2. Multiscale residual networks

By using convolutional layers with various scales to extract rich multi-scale information, the issue of single-scale convolution kernels' narrow receptive field is successfully solved. For example, Fu et al. [26] suggested a multi-scale residual pyramid attention network (MSRP) for the fusion of medical images that extracts features at various scales using convolutional layers with various kernel sizes and has improved feature extraction and expression capabilities. For recognizing stationary individuals and animals in the presence of obstructions, Ma et al. [27] presented a multi-scale residual attention network (MSRAN). The primary branch of the network's feature extraction module is a multi-scale learning structure with parallel 33 and 55 convolutional layers that learn fine-scale and coarse-scale features, respectively. The feature extraction module of the network is composed of 5 detail blocks with stacked multi-scale structures.

3.3. Stochastic deep networks

Aiming at the problem that deep networks have a strong expressive ability but are more difficult to train, Huang et al. [28] proposed stochastic deep networks (SDN). The generalization ability of ResNet can be significantly improved by randomly dropping some residual units during training to turn a deep network into a shallow network.

3.4. Multipath residual networks

To combat the issue of vanishing gradients and optimize network parameters, using multiple pathways for feature extraction has proven to be effective. Zhang et al. [29] presented the unique method known as ScaleNet, which makes use of stacked convolution-deconvolution blocks and a multi-path residual structure. The latter increases parameter efficiency by including skip connections between every two adjacent convolution-deconvolution blocks as well as inside each block. Liu et al. [30] suggested a cascaded dual-channel residual network (CDP-ResNet) that makes use of a residual block-based dual-path network to improve the segmentation of lung nodules in CT images. It consists of a 77 local path with a lower receptive field and a 1313 global path with a wider receptive field. To fuse characteristics from both pathways, a residual block is added after the first residual block of the local path.

3.5. Wide residual network

The wide residual network was designed to improve network performance by increasing the number of channels of the feature map, thereby widening the network. To achieve this purpose, a learning mechanism based on an extended channel number was proposed by [31,32], resulting in a wide residual network (WRN). Shi et al.'s [23] further suggestion for an innovative progressive wide network for MR image reconstruction was the Fixed Skip Connection-based Progressive Wide Residual Network (FSCWRN). The FSCWRN employs fixed skip connections and a progressive wide network instead of a deeper network, leading to better reconstruction performance than other state-of-the-art algorithms.

3.6. Recurrent residual networks

The network is made up of recursive blocks of weight-shared residual units, which enables recursive learning to reduce network parameters while increasing the number of layers, ultimately leading to improved network performance. For example, for single image super-resolution, Deep Recurrent Residual Networks (DRRNs) deepen the network while using recursive learning to manage model parameters [33,34]. While this was going on, Jin et al. [35] presented the Dual-Stream Recursive Residual Network (STRRN), which combines recursive learning with global, local, and multi-path intermediate residual learning to construct a multi-path recursion on each stream residual network. Gradient flow and the transmission of low-level features are made easier by this method, which also lowers the number of parameters.

3.7. Residual network in the residual network

Zhang et al. [34] developed Residual Networks of Residual Networks (ROR) inside Residual Networks to improve the optimization capability of residual networks beyond simply stacking residual blocks. ROR increases the residual network's capacity for learning by including hierarchical shortcut connections into the original residual network and swapping out the original residual mapping with the optimized residual mapping.

4. Application in disease diagnosis

With the introduction of large-scale picture data and the rapid increase in CPU capacity, remaining neural networks [36,37] have achieved amazing progress in the fields of computer vision and image processing. Researchers have used this technology in the area of medical imaging because of its outstanding feature learning capabilities [38]. A thorough analysis of the research on deep learning in medical picture classification, detection, segmentation, registration, and retrieval was carried out by Litjens et al. [39]. The advancement of medical picture computer-aided diagnosis is now being driven by medical clinical demands. Computer-aided diagnosis, according to Zheng et al. [40], can increase the precision of diagnoses, reduce the frequency of false positives, and offer clinicians efficient decision assistance. It can improve processing speed while also providing support analysis for subsequent doctors to assess a patient's condition. This section gives a general overview of the use of residual neural networks in the medical imaging diagnosis of lung tumors, skin conditions, breast cancer, and brain disorders. The residual neural network structure diagram in disease diagnosis is shown in Fig. 10.

4.1. Application of ResNet in the diagnosis of lung tumors

One of the malignant tumors with a high morbidity and death rate is lung cancer. Lung cancer is a severe hazard to human health since it occurs more often every year, according to a vast number of datasets [41]. However, it can be challenging for medical professionals to promptly recognize and diagnose lung cancer patients since its early clinical signs are not always clear. When the condition is identified, it is already advanced cancer. Therefore, the key to treating lung cancer is early identification and diagnosis. The classification and diagnosis results of lung tumors can be improved by improving the learning algorithm of the residual neural network. Its improvements include particle swarm optimization convolution kernel combined with gradient descent method to fine-tune the network, focal loss function optimization network, mixed loss function, etc.

Lung tumor research extensively employs residual neural networks. Liang et al. [42] have introduced a lung tumor image recognition algorithm, known as PSO-ConvK, based on particle swarm optimization (PSO) convolution kernel. They create a convolutional neural network (CNN) using the parameter transfer approach to extract the convolution kernel as the starting population. To find the overall best solution, the PSO is used to initialize the CNN, and each particle's position and speed are updated. Gradient descent is

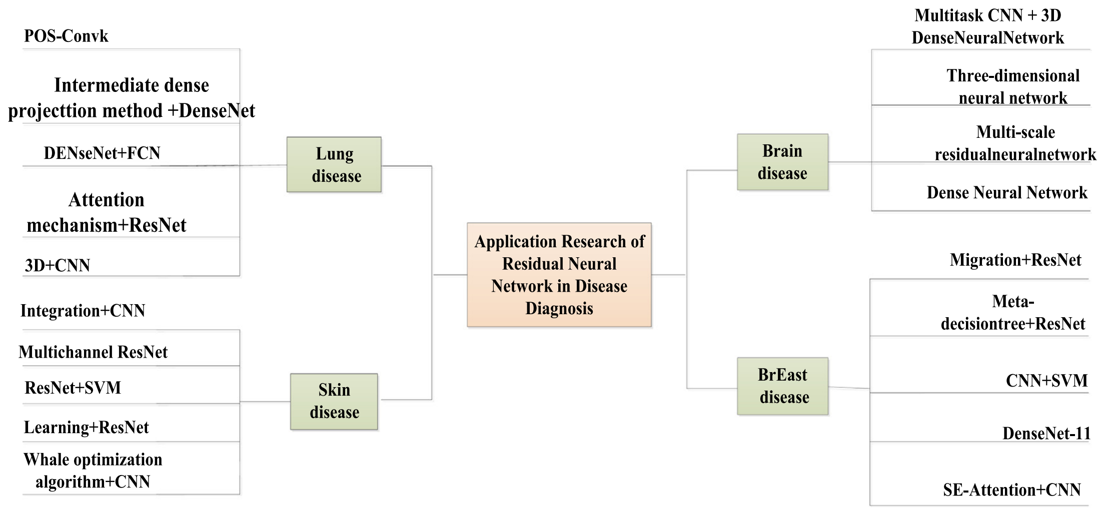

Fig. 10. Residual neural network structure diagram in disease diagnosis.

used to fine-tune the network once the CNN has been trained using CT scans of lung tumors. A residual neural network was used by Nibali et al. [43] to categorize benign and malignant lung nodules. They employed the ResNet architecture to investigate the impact of transfer learning and various network depths on the accuracy of malignant tumor classification.

An enhanced pulmonary nodule classification and identification method based on a dense network were proposed by Dai et al. [44]. The model is based on DenseNet and obtains 3-dimensional data on lung nodules using the intermediate dense projection approach. The network is trained using focal loss so that it can concentrate on understanding similar lung nodules. Yao et al. [45] proposed a strategy for identifying lung nodules by using a 3D fully convolutional network based on mixed loss and an attention-based multi-scale 3D residual network. A multi-scale attention-based 3D residual convolutional network is used to classify suspected nodules and precisely distinguish true nodules from candidate nodules.

Zhu et al. [46] published an improved U-Net convolutional neural network lung nodule diagnosis method. High-speed feature information travels between the input and output layers via a dense network that employs convolution and pooling operations to generate high-level features. To improve the usage of low-level lung nodule characteristics, dilated convolution is mixed with multi-scale features. In a computer-aided diagnostic (CAD) system, 3D computed tomography images were used by Zhang et al. [47] to classify lung nodules. Various CNN models compare the 3D CT images. Studies reveal that for the categorization of lung nodules, DenseNet121 and Xception both produced superior outcomes.

4.2. Application of ResNet in the diagnosis of skin diseases

Melanoma is malignant skin cancer caused by melanocytes. One of the deadliest and most common skin cancers is malignant melanoma. Melanoma is treatable if identified and treated well in its early stages. The results of the classification and diagnosis of skin diseases can be improved by improving the learning algorithm of the residual neural network. Its improvements include integrated ResNet, feature-level fusion, whale algorithm optimization, etc. Residual neural networks have been extensively studied in skin disease diagnosis research. To combine the results of the classification layers of four distinct deep neural network designs, including AlexNet, GoogLeNet, VGG (visual geometry group), and ResNet, Harangi used an ensemble technique. The weighted output of the CNNs is used for the final classification to obtain high classification accuracy. Guo et al. [48] proposed a paradigm for skin damage analysis using a multi-channel residual neural network. The fundamental concept is to link the feature layers in several residual neural networks (Res-Nets) created from the pictures to obtain the final prediction result.

A deep residual network-based approach for melanoma identification in dermoscopic pictures was put out by Li et al. [49]. Support vector machines (SVM) are utilized to categorize the recovered melanoma characteristics after pre-trained ResNet-152 is used to extract deep features from pictures of skin lesions. With little training data, the technique solves the issue of significant intra-class differences in melanoma and minor inter-class differences between melanoma and non-melanoma. Hu et al. [50] aimed at the problems of low contrast and large information interference in the classification and recognition task of melanoma. An ensemble classification method using mask-based data augmentation combined with deep residual neural networks. This ensemble classification model makes up for the shortcomings of a single residual neural network in melanoma classification.

4.3. Application of ResNet in breast diagnosis

Breast cancer, one of the most common malignant tumors in women, has a significant effect on the physical and mental well-being of women and even puts their lives in danger. The results of breast disease diagnosis can be improved through the improvement of the residual neural network learning algorithm, which includes imbalance processing of the dataset, data enhancement, random cropping, and angle rotation. A residual neural network is widely used in breast diagnosis research.

To identify tumors in mammography pictures, Chougrad et al. [51] extracted the region of interest for preprocessing before utilising the transfer learning approach to hone ResNet. With the use of a deep residual neural network, Gandomkar et al. [52] split benign pictures into 4 categories and malignant images into 4 subtypes for a multi-classification task involving breast histopathology images. For categorisation, the results of pictures processed with various magnification factors are pooled.

Breast tumors that were benign and malignant were found by Chu et al. The dataset is unbalanced, and the amount of data is increased, features are extracted using convolutional neural networks, SVMs are employed for classification, and the classification F1 scores of the CNN's feature maps are then computed [53].

The fine-tuning node is chosen from among the layers with the best classification performance, and then the newly built two-layer fully linked layer is joined to create the new network. Li et al. [54] developed the DenseNet-II neural network model for the accurate classification of benign and malignant breast images. In DenseNet-II, the Inception structure takes the role of DenseNet's first layer convolution, keeping the sparseness of the network structure. Deng et al. [55] created a CNN model paired with an improved SE-Attention mechanism for the identification of breast cancer sickness. The network may selectively increase beneficial features while suppressing unhelpful features thanks to the enhanced SE-Attention mechanism, resulting in effective learning of features. Experiments show that the performance of Inception-V4 and DenseNet networks based on SE-Attention has been greatly improved.

4.4. Application of ResNet in the diagnosis of brain diseases

Alzheimer's disease (AD) is a degenerative brain disorder that results in permanent memory loss and cognitive decline. Early detection of AD is of utmost importance for patient care and treatment, as there is currently no effective cure for the condition. Magnetic resonance imaging (MRI) is a valuable tool for assessing brain morphological changes in the diagnosis of AD, as well as monitoring and treating the pathological progression of the disease. There has been extensive research on using residual neural networks [56] for the diagnosis of brain disorders.

Li et al. [57] proposed a dense convolutional neural network-based classification method to classify AD by learning various local characteristics of MRI brain images. Liu et al. [58] developed a multi-scale residual neural network in order to collect multi-scale information about images and perform residual learning on the neural network. A 3D deep residual neural network was suggested by Murad et al. [59] to extract the distinctive features of brain anatomy from 3D pictures and develop a brain age prediction model.

Zhao et al. [60] introduce a novel U-Net method for the segmentation of cardiac chambers in magnetic resonance images with ghost artifacts. The ghosting artifact is a common artifact in MRI that can interfere with the accurate segmentation of cardiac structures. It is therefore important to develop methods that can handle such artifacts and achieve accurate segmentation.

A residual network based on voxelwise that incorporates multi-modal and multi-level context data into the network was proposed by Chen et al. [61]. To accurately segment the anatomy of the brain, characteristics of various scales are retrieved using the complimentary data from several modalities. The multi-task deep model and DenseNet integrated deep network by Liu et al. [62] were designed for AD classification, and the network employed a multi-task deep CNN model to produce image multi-level features. After identifying diseases using features it has learned from photographs of the disorders, a deep 3D DenseNet model incorporates the qualities it has learned to categorize sickness phases. The application of deep learning in the field of cardiovascular imaging diagnosis has both potential and challenges. Deep learning is a machine learning approach that can automate image diagnosis by learning large amounts of data and building complex neural network models [61] (Table 1).

ResNet offers a wide range of possible applications in the field of medical image processing, including:

1) integrating different network forms: ResNet can be combined with other network structures like Inception, DenseNet, etc. to increase the model's expressiveness and generalizability as well as its performance.

Table 1
The specific architecture of the pyramidal residual network.

Network layer	Output size	Residual unit
Conv1	32*32	[3*3,16]
Conv2	32*32	[3*3,16+α(k-1)/N 3*3,16+α(k-1)/N]*N_2
Conv3	16*16	[3*3,16+α(k-1)/N 3*3,16+α(k-1)/N]*N_3
Conv4	8*8	[3*3,16+α(k-1)/N 3*3,16+α(k-1)/N]*N_4
Avg-pool	1*1	[8*8,16+α]

2) Combining multimodal data: Combining medical image data from many modalities helps increase the model's stability and accuracy. Additionally, by including other auxiliary data, such as clinical data, genetic information, and medical records, the model's predictive power can be increased even further.
3) Solving the labeling inaccuracy problem: Using techniques like semi-supervised learning and weakly supervised learning, the problem of inaccurate medical image labeling may be resolved, and the generalizability and robustness of the model can be further enhanced.
4) Enhancing model interpretability: The discipline of medical image processing places a premium on model interpretability. Consequently, visualization techniques, interpretable neural networks, and other techniques can enhance the model's credibility and interpretability to further increase the model's applicability value.
5) Lightweight models: In some cases where resources are limited, lightweight models can enhance the performance and speed of the simulations. Because of this, it is possible to create a lightweight ResNet model using methods like network pruning, parameter sharing, and deep separable convolution to increase the model's usefulness.

5. Conclusion

The paper identifies some of the problems of residual neural networks in medical image processing and suggests future directions for development. Among them, the future development directions may include further improving and optimizing the residual neural network model to improve its accuracy and efficiency in medical image processing; exploring more applications in medical fields, such as heart disease and kidney disease; and solving the problems of the small amount of data and difficult labeling of medical images to improve the generalization ability of the model and the feasibility of practical applications. The remaining neural networks have helped deep learning progress. As a result, this paper provides an overview of the research's history and the significance of the residual neural network. Four applications of residual neural networks in the field of medical image processing are discussed, together with their basic concept and network structure: the identification of lung tumors, the diagnosis of skin conditions, the detection of breast cancer, and the detection of brain disorders. In addition to providing a resource for clinical computer-aided diagnostics, it helps doctors make informed medical judgments and improves patient prognoses. Despite developments in medical imaging, residual neural networks will continue to be crucial in the years to come. There are still many obstacles to overcome, and the following issues demand urgent research:

1) The application and exploration of the ResNet network in medical images are only in their infancy. Because the neural network itself has characteristics that are difficult to explain. This is very unfavorable for the special field of medicine, so neural networks are currently mainly used to assist medical diagnosis and disease prediction.
2) The prediction ability of the ResNet network model needs to be verified by more clinical experiments. To achieve this, we not

only need more medical image data to validate the model but also need to build a more accurate and powerful neural network model.

3) Medical images often contain a lot of private information about patients. Therefore, how to obtain the patient's permission and how to make full use of this medical image information under the condition of protecting the patient's privacy is also a major difficulty in this field. However, I believe that the development of technology, neural networks, and artificial intelligence will bring huge changes to the medical industry, and more people will benefit.

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Declaration of Competing Interest

The authors declare that there is no conflict of interests in this article.

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