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Cloud image cloud detection based on multidimensional dense connected convolutional neural network

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ABSTRACT: In the field of computer vision, convolutional neural network is gradually superior to other traditional methods and has become the mainstream algorithm. With the rapid development of convolutional neural network, lenet, alexnet, vggnet and other models are widely used in computer vision tasks. However, with the deepening of the number of layers of the network model, the forward signal and gradient signal of the network model gradually disappear after many layers in the training process. At present, many improved network models have been proposed to solve this problem, such as RESNET, highway network [2], fractalnet [1], etc. its essence is to solve the problem of signal transmission disappearance by creating cross layer connections. The dense connected convolutional neural network in this section is to design a new connection mode to optimize the information transmission between layers in the network. According to the channel characteristics of multispectral satellite cloud images, a multidimensional dense connected convolutional neural network (m-densenet) is proposed by adding dimensions to the original dense connected convolutional neural network model, It enhances the learning ability of the model for the characteristics of satellite cloud images.

KEYWORDS: Densely connection network; Redundancy; M-densenet; Deep Learning

I. INTRODUCTION

Satellite cloud image cloud detection is the key to the analysis and application of various remote sensing data, however, due to the high complexity of certain specific categories of features and remote sensing data in different bands has many correlations, which improves the difficulty of the model in feature learning. The utilization of multi-spectral image features in the existing models is low, which results in low accuracy in cloud detection. On the basis of investigation and analysis of domestic and foreign scholars, it is found that convolutional neural network has a very good learning ability for image features, and the paper focuses on the application of Deep Learning in cloud detection of satellite cloud images.

This paper describes the status quo and research significance of satellite cloud image cloud detection at home and abroad firstly. Then the paper introduce the limitations of traditional methods in the application of satellite cloud images and the good results have achieved by Deep learning in the field of images in recent years, and then the Deep Learning technique is applied to the research of satellite cloud image detection.

In the process of deep learning, with the deepening of deep learning network, the deep learning network can extract features effectively, but there are some problems in training, such as vanishing gradient problem, low training efficiency and difficulty in optimization. In order to solve these problems, this paper uses Multidimensional densely connected convolutional neural network model to realize cloud detection of multi-spectral satellite cloud image, because it is not highly utilized in feature channels, this paper proposes a dense connected convolution neural network model based on attention mechanism to realize cloud detection of multi-spectral satellite cloud images, which effectively combines the attention mechanism with the densely connected convolutional neural network. It makes the use of features of the model reach the maximum. In order to improve the performance of the densely connected convolution neural network model with attention mechanism, we adopt the way of shared storage space to reduce the appearance of the model and make it possible to use a deeper network structure in the case of limited computing resources; Combined with the improved optimizer, the learning rate is dynamically trimmed, which makes the model perform better. The experimental results show that the densely connected convolution neural network model based on attention mechanism also performs well in the application of cloud detection with complex spectral information.

II. DENSE CONNECTION DESIGN CONCEPT

The milestone breakthrough in the history of CNN comes from the emergence of deep residual convolutional neural network (RESNET). The core of deep residual convolutional neural network is to optimize the back propagation of gradient by establishing "short circuit connection" between the front and back layers, so that the model can train deeper networks. The basic idea of dense connected convolutional networks (densenet) is consistent with the depth residual convolutional neural network. The main difference in model structure is that the dense connected convolutional neural network establishes the dense connection between all the front layers and the back layers. The network structure of densely connected convolutional neural network has a more radical connection mode than that of deep residual convolutional neural network.

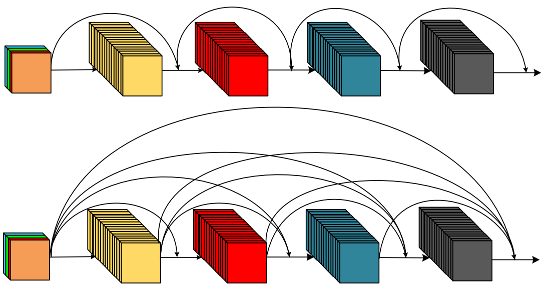

Figure 1 Comparison of connection modes between RESNET (upper) and densenet (lower)

As shown in Figure 1 above, the depth residual convolutional neural network is that each layer is short circuited with a previous layer and connected in the way of element addition, but each layer in the densely connected convolutional neural network will be connected with all previous layers in the channel dimension as the input of the next layer. For a layer of network, the densely connected convolutional neural network has a total of connections. Compared with the depth residual convolutional neural network, the densely connected convolutional neural network is denser in network connection than the depth residual convolutional neural network, and the densely connected convolutional neural network can realize the reuse of features by merging the feature maps of different layers, Compared with the depth residual convolution neural network, it can improve the efficiency, which is also the most essential difference between the design concept of densely connected convolution neural network.

III. MULTIDIMENSIONAL DENSE CONNECTED CONVOLUTIONAL NEURAL NETWORK MODEL

As shown in Figure 2, it is the detailed diagram of the multi-dimensional dense connection module, which represents the characteristics of the input cloud image, the composition function and the transformed output. For the multi spectral satellite cloud image, the dimension of the model is improved.

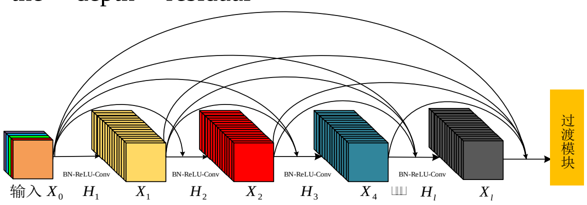

Figure 2 Detailed drawing of dense connection module

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3.1 Dense connection mode

The traditional forward connection of convolutional network generally takes X_l as the input and X_{l+1} as the output. However, with the deepening of stacking layers, there will be a common problem of gradient disappearance. At present, the common method to solve the gradient problem is to solve it through standard initialization and regularization. However, when the network convergence and gradient signal blocking are solved, the model will degenerate. With the increase of the depth of the neural network, the accuracy of the model begins to saturate, and then it will decline rapidly. Accuracy degradation shows that the deep structure with more layers by increasing the number of layers can not improve the accuracy. The core problem is that the added layers are self mapping, and other layers are copied from the shallow model, so this model will not improve the accuracy. The deep residual network solves this problem we.

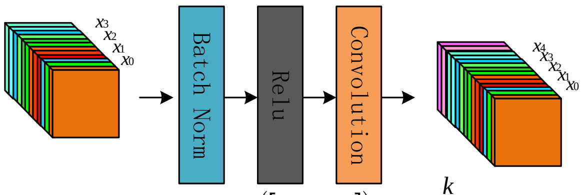
Let the added layer coincide not with a mapping, but with the residual mapping. The output of layer $l-1$ of the depth residual neural network is equal to the nonlinear transformation of the output of layer I plus layer $l-1$.that is:

$$X_l = H_l(X_{l-1}) + X_{l-1} \quad (3\text{-}1)$$

The dense connection network is further improved on the basis of the deep residual network. The output of layer I is equal to combining the output characteristic diagrams from layer 1 to layer I-1, and then making nonlinear changes, that is:

$$X_l = H_l([x_1, x_2, ..., x_{l-1}]) \quad (3\text{-}2)$$

3.2 Network model growth rate



$x_4 = h_4([x_0, ..., x_3])$

Figure 3 growth rate

As shown in Figure 3,k characteristic graphs will be generated after each compound function operation, and there will be l characteristic graphs when the number of layers is $l \times k$. The value of represents the amount of information circulating in the network. The larger the value, the greater the information circulating in the corresponding network, and the stronger the expression ability of the network. However, the value of can not be too large, otherwise there will be too many network parameters, resulting in problems such as too large size and too many parameters of the model.

3.3 Network model optimization

1. Bottleneck layer

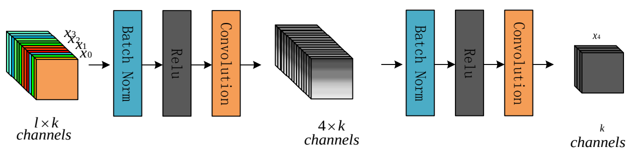


Figure 4 Comparison of video memory usage of different layers and different storage methods

As shown in Figure 4 above, due to the large input of the later layer, the dense connection module mainly adopts the bottleneck layer to reduce the amount of calculation, that is, a convolution layer with dimension 1×1 is added on the basis of the original structure. Densenet-b structure is composed of batch standardization layer, relu layer, 1×1 convolution layer, batch standardization layer, relu layer and 3×3 convolution layer. 1×1 convolution layer obtains $4\times k$ characteristic map, which further reduces the number of features and improves the calculation efficiency.

2. Coefficient of compressibility

The transition module includes a 1×1 convolution layer and a 2×2 average pool layer. The main function of the transition module is to

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connect the adjacent dense modules and reduce the size of the feature map, so as to compress the model. If m characteristic diagrams of the dense connection module are connected in front of the transition module, the transition module can generate $\theta \times m$ characteristic diagrams ($\theta \in (0,1]$), where θ refers to the compression coefficient. When θ is less than 1, the structure of the model is densenet-c. for the dense connection module using the bottleneck layer and combined with the transition module with the compression coefficient less than 1, the structure is called densenet-BC.

IV. MODEL CHARACTERISTICS

The traditional optimization method adopts the error back propagation algorithm. The error signal will be displayed only in the last layer, and then transmitted from the output layer to the input layer layer layer by layer, resulting in the weakening of the supervision of the first few layers, which makes the optimization efficiency low.

The idea of the model is to increase the cross layer connection. There is a connection between any two layers. The first layer contains the input of the previous I-1 layer, which turns a one-dimensional linear structure into a plane network with many cross layer connections. When the error signal is calculated to be transmitted forward and backward in the last layer, the dense connection can transmit the error signal to any previous layer faster, The gradient dissipation will be greatly weakened, making the depth of supervision deeper and improving the optimization efficiency.

After each layer of the traditional neural network is refined based on the features of the previous layer, it continuously transmits the newly learned features to the next layer, constantly refining the features, from the low-level features to the high-level features to the final output. If there are few feature maps in one layer, the traditional neural network will not be able to optimize the few feature maps. Because the output of any layer of the densely connected network can be used by other layers, and the previous features, such as the features of the first layer, can be reused by any layer in the future. In this way, each layer only needs to learn few features, resulting in a significant reduction in the amount of calculation of each layer and the parameter scale of the network.

From the perspective of machine learning, there is a smooth hypothesis. When two models reach the same training error, give priority to using a function with smoother decision surface to reduce the occurrence of over fitting, so that its generalization performance will be better. Neural network is essentially a composite function. Each transformation is equivalent to a composite. Multiple composite will lead to the complexity of the decision function. For traditional neural networks, our classifier function is based on the most complex features, that is, the output of the last layer. The expression of the classifier function is:

$$Y = H_l(x) \qquad (3\text{-}3)$$

Dense connection uses all features from simple to complex. It can not only use the most complex features, but also reuse simple features. Therefore, the classifier function obtained by dense connection network will be the smoothest. The expression of classifier function is:

$$Y = H_1(x) + H_2(x) + ... + H_l(x) \qquad (3\text{-}4)$$

Therefore, densely connected networks will also perform well on small data sets, and have stronger generalization ability than traditional convolutional neural networks.

V. COMPARISON OF RELEVANT EXPERIMENTS

5.1 Cloud image dataset

In order to verify the improved effect of the model in this article, this section adds an experimental comparison between the improved SE-DenseNet and M-DenseNet. The data comes from the China Resources Satellite Application Center, which is one of the three major satellite application centers in my country. The collection of cloud images mainly comes from HJ-1A/1B satellite images. Meteorological experts select 9600 thick cloud samples, thin cloud samples, and cloudless samples from the original cloud image as the data set, of which 8000 samples are taken as the training set. The remaining samples of the class sample are used as the test set, and the pixel size of each sample is 28×28.

5.2 Comparison of simulation results

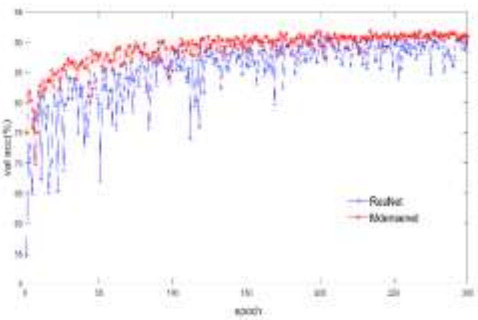

Figure 5 verification accuracy curve of M-DenseNet and RESNET

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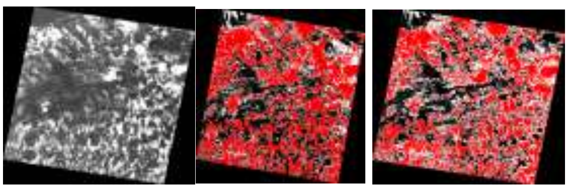
This simulation experiment uses a 121-layer multi-dimensional densely connected convolutional neural network (M-densenet) and a 152-layer deep residual convolutional neural network (ResNet) for comparison. Deep residual networks only rely on the most complex features of the network, while multi-dimensional densely connected convolutional neural networks utilize not only the most complex features, but also shallow features. Figure 5 shows the validation accuracy trends of deep residual convolutional neural networks and multi-dimensional densely connected convolutional neural networks on the Cloud dataset. In the first 50 iterations, the multidimensional densely connected network converges significantly faster than the convolutional neural network. And in the first 75 iterations, the validation accuracy of the multi-dimensional densely connected convolutional neural network is already close to 90%, while the validation accuracy of the deep residual convolutional neural network is close to 90% after 150 iterations. Densely connected convolutional neural networks significantly better than deep residual convolutional neural networks.

In order to enhance the contrast of the experiment, the cropped multispectral satellite cloud images are put into the trained model to be predicted, and then each satellite image is spliced in the form of pixels, so as to realize the overall prediction of satellite cloud images. The performance of the model can be evaluated intuitively. This simulation uses the point cloud experiment effect comparison chart. As shown in Fig. 6, no cloud is marked in black, thick cloud marked in red, and the thin cloud marked in white. From Figure 6, we can find that the deep residual network model has over-detection of thick cloud and false detection of thin cloud in the upper left corner, while the multi-dimensional densely connected convolutional neural network in this paper can better complete different types of cloud image recognition, but mistakes are still inevitable. The false detection of thin cloud, shown in the upper left corner, illustrates that the multi-dimensional densely connected convolutional neural network still needs improvement.



(a)Original satallite cloud map (b) ResNet (c) M-densenet

Figure 6 Comparison of cloud detection effects of different methods

VI. CONCLUSION AND DISCUSSION

This paper introduces the importance of convolution and dense connection in the training of neural network. Aiming at the problem of parameter quantity caused by dense connection, two solutions are proposed, that is, the parameter quantity is effectively reduced through bottleneck layer and compression coefficient. The characteristics of dense connection in model training are studied, such as high optimization efficiency, small parameter scale and strong generalization ability. Relevant experiments are carried out to further verify the superior performance of multi-dimensional dense connection. Although the multi-dimensional dense connected convolutional neural network in this section has better completed the detection of different kinds of clouds, there is still room for improvement in the overall performance.

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