# Cloud Recognition Based on Lightweight Neural Network

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***Abstract*— Cloud type recognition is a basic task in the field of ground-based cloud meteorological observation. It is of great significance to identify cloud type accurately for improving the accuracy of weather forecast. In this paper, we propose a new lightweight convolutional neural network model, called LCCNet, to achieve accurate cloud recognition of ground-based cloud images. We build a standard ground-based cloud data set contains 11 categories, called HBMCD, which is recognized by professional meteorological stations and conforms to the standards of the World Meteorological Organization. Compared with other existing ground-based cloud data sets, HBMCD have larger data volume, complete cloud categories and uniform quality, and are more professional and comprehensive. A number of comparative experiments demonstrates that the proposed LCCNet model has stronger characterization ability and higher classification accuracy, which is up to 97.35%. At the same time, its parameter amount and operation complexity are lower than the existing network models, which makes it possible for equipment integration and practical application.**

## I. INTRODUCTION

Cloud is an important part of the earth's thermal balance and hydro-gas cycle, and the shape of cloud reflects the stability of atmospheric motion and weather characteristics, which is one of the main features of predicting future weather changes. According to the shape characteristics, structure characteristics and cloud bottom height, clouds can be divided into ten categories. Accurate recognition of cloud shape can help us effectively improve the accuracy of weather forecast, the effectiveness of climate model prediction and understand global climate change, which is of great significance [1]. At present, most meteorological stations rely on the identification of the foundation cloud by the weather observer, but the artificial identification is easily affected by subjective factors such as the observer's mood, observation experience, etc. In addition, due to the non-rigid structure of the cloud and its unpredictable shape, the huge workload of manual observation makes it difficult to ensure the continuous observation for a long time, which restricts the accuracy of cloud recognition [2]. Therefore, how to use the technology of digital image processing and pattern recognition to realize the automatic recognition of cloud shape, and how to deploy and apply it in the meteorological station has become a research hotspot in the field of meteorology. [3-5].

## II. RELATED WORK

Automatic cloud identification technology can be divided into two aspects: satellite cloud image and ground-based cloud image [6]. Compared with satellite cloud images, ground-based cloud images have higher spatial resolution and richer local cloud information [7]. Therefore, automatic cloud identification based on ground-based cloud images is attracting more and more attention. Scholars at domestic and abroad have carried out relevant researches and achieved certain results. Han wenyu et al. used the sparsity of cloud image gray scale to identify 5 types of cloud images, with an average accuracy of 82.8% [8]. However, the reconstruction performance of this algorithm was weak, and only the typical cloud images with high discrimination could be recognized, and the similar cloud images such as stratified clouds and cumulonimbus clouds could not be distinguished. Li chenxi et al. conducted scaling analysis on the gray scale data of cloud images by extended self-similarity (ESS) model. 150 cloud images of 5 categories were identified by using scaling features of different cloud systems, with an accuracy rate of nearly 90% [9]. However, due to the limited number of test samples, the robustness of the algorithm could not be verified. Zhang chi et al. proposed a cloud image recognition method based on visible light and infrared image information fusion, and identified 5 kinds of cloud images, with an average accuracy of 82% [10]. Because this algorithm requires comprehensive consideration of the whole sky cloud image and infrared cloud image, the recognition conditions are harsh and the applicability is not high. Since the traditional image recognition algorithm cannot adapt to the changeable characteristics of cloud, and the recognition types are few and the accuracy is low, scholars turn the center of gravity of cloud recognition to the deep learning method. Zhao liangliang et al. used convolutional neural network for cloud recognition, proving that convolutional neural network has higher detection accuracy than traditional classification methods [11]. Zhong Zhang et al. proposed the transmission depth local binary mode (TDLBP) and weighted metric learning (WML), combined with convolutional neural network, to identify cloud images collected from different perspectives with an accuracy rate of nearly 80% [12]. Jinglin Zhang et al. constructed a new convolutional neural network model CloudNet, which can recognize 11 kinds of cloud images with an accuracy of 88% [13]. However, the data set used in network training is small and only contains 2543 cloud images, which may lead to false high accuracy caused by over fitting. With the rapid development of artificial intelligence, all kinds of image recognition technologies have become mature [14-16]. However, there are not many studies on cloud image recognition based on ground-based cloud image. And the existing achievements generally have the following deficiencies: 1. Neural network method requires high quality and quantity of data set, but the existing cloud image data set is too small, and the image resolution and angle are different, which will lead to low confidence and poor comparability of experimental results to some extent; 2. The accuracy of traditional recognition methods is low, and the types of recognition are incomplete; 3. The existing cloud recognition methods based on deep learning have large parameters, high computational complexity, and are not convenient for practical application, and the accuracy still needs to be improved [17,18].

In conclusion, the research and design of a technology that can accurately and automatically identify multiple clouds is of great significance to improve the accuracy of weather forecast, flight support, analysis of regional climate characteristics, and has great application value. Considering the outstanding performance of convolutional neural network in the field of image recognition and the sensitivity of this method to data, this paper first collected and screened a large number of ground-based cloud images with special equipment, and under the guidance of professionals in the industry, constructed a large-scale, consistent shooting angle and uniform quality ground-based cloud image data set HBMCD (HUAYUN BJUT-MIP Cloud Data set), covering 10 standard cloud genera and sun (cloudless), with the number reaching 38209. Therefore, it can guarantee the confidence and comparability of subsequent experiments. Based on this data set, this paper proposes a lightweight cloud recognition network model LCCNet (Light Cloud Classification Net), which can extract more targeted features of the cloud. At the same time, under the premise of ensuring high recognition accuracy, the amount of parameters and calculation of the model is greatly reduced. The work of this paper solves the problems of low number of existing research data sets, few types of recognition, low accuracy, large amount of network model parameters, which lead to the high proportion of video memory. To a greater extent, it ensures the accuracy of weather prediction through cloud recognition, and provides the possibility for the actual deployment of the algorithm.

The structure of this paper is as follows: the third part introduces the construction and comparison of HBMCD, the fourth part introduces the construction of LCCNet, the fifth part shows and analyzes the experimental results of LCCNet.

## III. The HBMCD Data Set

### A. *Classification of Ground-based Cloud Image*

Cloud shape refers to the physical characteristics of clouds. According to the shape, composition and cause of formation of clouds, clouds are divided into Cumulus, Cumulonimbus, Stratocumulus, Stratus, Nimbostratus, Altostratus, Altocumulus, Cirrus, Cirrostratus and Cirrocumulus. According to the height of the ten genera, they can be divided into three groups: low cloud group, middle cloud group and high cloud group [17].

The classification and characteristics of cloud genera are shown in Table I.

### B. *Building HBMCD Data Set*

(1) Source of original data

Due to the experimental data of this paper is provided by HUAYUN SOUNDING (Beijing) [10] meteorological technology limited liability company. And the original data is unclassified cloud chart. Under the guidance of professional meteorologists, the initial cloud image data set is formed by artificial classification. This data set is composed of 11 cloud maps (10 clouds and sun), with a total data amount of 10942 ground-based cloud maps with a resolution of 1358×1358. Its composition is shown in Table II.

(2) Data set construction of HBMCD

This paper constructs the data set through three steps, and the overall process is shown in Fig.1. First of all, under the guidance of professional experts, the collected pictures are manually classified to form a basic data set, and the data set is used for migration learning, as shown in Fig.1(a); Then, the migration learning model with the best effect is used for auxiliary verification of the data set, and the pictures with wrong classification and low classification confidence rate are manually screened twice, as shown in Fig.1(b). Then add new pictures step by step, repeat these two steps until the confidence rate of the whole data set reaches 95%; Finally, carry out data enhancement operation, expand the data volume, as shown in Fig.1(c), and form the final large-scale standard cloud chart data set HBMCD.

The specific construction method of data set is as follows: in the first step, the original images are screened to make the images evenly distributed in different conditions, such as light, weather conditions, seasons, etc. The data set is divided into 10 types of cloud genera and 1 type of cloudless according to the standard of the international meteorological organization. In order to ensure higher accuracy, this paper uses five classic network models: VGG16 [17]、VGG19、Inception-V3 [20]、ResNet-152 [21]、DenseNet-201 [22] to carry out migration learning training with the same experimental configuration, and selects the optimal effect of each network model for comparison[23]. The comparison of the optimal test results of each network model is shown in Table III. According to the comparison, DenseNet-201 has the highest accuracy when unfreezing layer 2 forward, reaching 96.55%. Therefore, this network is selected for the second step of auxiliary verification.

In the second step, this paper sets the maximum probability of SoftMax output in DenseNet-201 network as the confidence level of the image in the model. The specific auxiliary verification method is to input a picture into the network and compare the predicted result with the actual label. If the classification is wrong, confirm its label again; if the classification is correct, observe whether its confidence is greater than 0.8; If it is greater than, temporarily consider the picture classification is correct, otherwise confirm its label again. Repeat the above process for many times to filter the initial data set, and continuously improve the confidence rate of the data set and the fitting ability of the migration learning model, until the correct number of pictures classified by DenseNet-201 accounts for more than 95% of the total number of pictures.

In the third step, considering that the data set is less and the data among different categories is extremely unbalanced, it is easy to cause over-fitting. In this regard, we use data enhancement to expand the data set. In this paper, six methods are used to enhance the undirected data of different types of cloud images, which are horizontal, vertical, fixed angle rotation, translation and random Gaussian noise processing. The final standard cloud image data set HBMCD is formed. The data volume of HBMCD data set is 3 times of the original data set. The composition of HBMCD data set is shown in Table IV.

### C. Data set comparison

As can be seen from Table V and Fig.2, the existing open source cloud map data sets are few, with low resolution and different cloud image quality. Although CCSN data set contains all cloud genera, due to its data collection from different angles, the images contain many interferences (trees, houses, etc.), resulting in different picture quality. HUST and SWIMCAT data set, however, contain incomplete cloud genus categories and are not classified according to the standard definition of cloud genus, with low reference value. The cloud pictures adopted in this paper is provided by professional weather stations, and the pictures are collected from the same angle. The cloud genus is divided according to industry norms, and the quality is uniform. Compared with other existing data sets, it has a higher reference value.

The data set is available at the web site:

https://github.com/SadaharuZL/HuaYun-BJUT-MIP-Cloud-Dataset

## IV. LIGHTWEIGHT CLOUD RECOGNITION NETWORK MODEL

### A. LCCNet network model

The structure of the cloud recognition network LCCnet designed in this paper is shown in Fig.3. Considering that Resnet-152, DenseNet-201 and other networks perform well in transfer learning, this paper also integrates some ideas of these networks in the design of cloud recognition network. Firstly, the shallow layer information is extracted through a layer of 3×3 convolution layer and pool layer, and then the network is constructed by repeating the stage module four times, where D is the down sampling unit and E is the feature unit. Each stage contains a different number of feature extraction units and a downsampling unit. Finally, feature classification is realized by convolution, global pooling and full connection layer. This design idea makes the network simple and easy to realize, and has strong expansibility. At the same time, in order to solve these problems, when designing LCCNet, on the premise of ensuring the recognition accuracy, this paper uses some techniques to reduce the model parameters.

TABLE I
CLOUD CLASSIFICATION TABLE

| Cloud class | Cloud genus: Scientific name | Cloud genus: Abbreviation | Cloud characteristics |
|---|---|---|---|
| Low cloud group | Cumulus | Cu | Having an upward projection of a circular arch; clouds similar in size to fists; margins clear. |
| | Cumulonimbus | Cb | Clouds are thick and broccoli-like; edges are blurred. |
| | Stratocumulus | Sc | Clouds are generally fist-sized and loosely distributed, clustered, traveling and wavy, often grey or gray-white. |
| | Stratus | St | Clouds lay evenly; cover a large area, almost all over the sky; mostly grey. |
| | Nimbostratus | Ns | Clouds are low and amorphous; often covered with the sky and completely obscured the sun and moon; clouds are fluffy and dark grey. |
| Middle cloud group | Altostratus | As | Clouds are thicker and covered with the sky; the sun passes through almost no halo; clouds often have striped structures and are grayish-white or grayish-blue. |
| | Altocumulus | Ac | Clouds are small and distinct in outline; thin clouds are white, visible Sun-Moon outline, thick clouds are dark gray, the outline of the Sun-Moon is not clear; clouds are oval, tile-shaped, fish scales or water wavy distribution. |
| High cloud group | Cirrus | Ci | Thin and transparent; white and shiny; the clouds are filamentous and horsetail-like. |
| | Cirrostratus | Cs | The bottom of the cloud has a filamentous structure; the cloud body is thin enough to pass through the sun and the moon; and there is a distinct halo under the sun's illumination. |
| | Cirrocumulus | Cc | Clouds are very small, white and shiny; they are thin white scales; they are often arranged in rows and in groups. |

TABLE II
HUAYUN SOUNDING CLOUD MAP DATA SET

| Cloud genus | Ac | As | Cc | Ci | Cs | Cu | Sc | Cb | Ns | St | Sun |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Data volume | 860 | 909 | 891 | 932 | 877 | 901 | 890 | 891 | 910 | 881 | 2000 |
| Total volume | 10942 sheets | | | | | | | | | | |

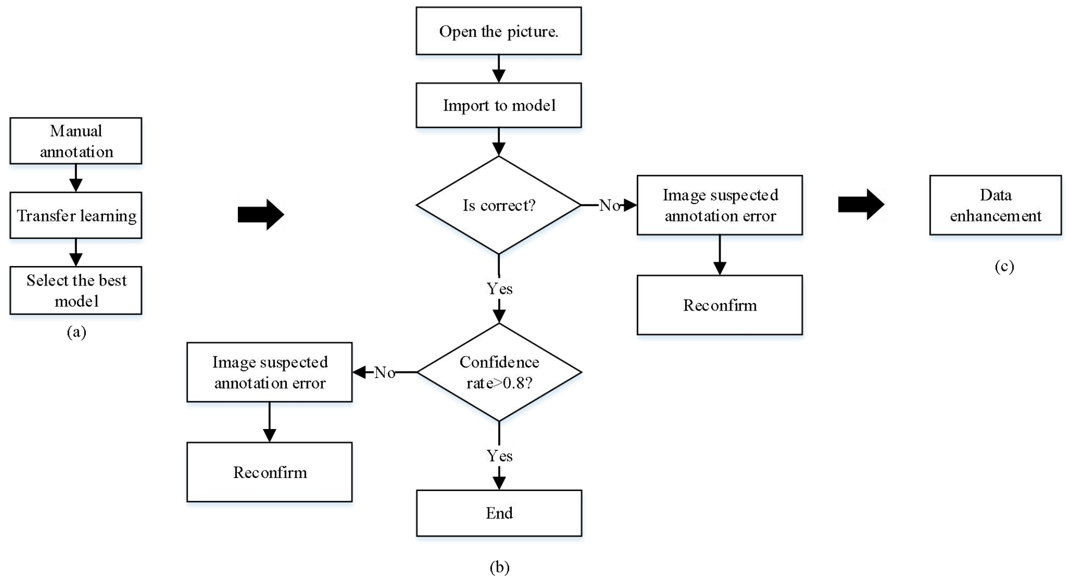


Fig.1. Data set building process: (a) Establish basic data set and select the optimal transfer learning model; (b) Aided verification; (c) Data enhancement.

TABLE III
COMPARISON OF TRANSFER LEARNING EFFECT UNDER DIFFERENT THAWED LAYERS

| The network model | Thawed layer | Testing set accuracy |
|---|---|---|
| VGG16 | 3 | 86.52% |
| VGG19 | 1 | 86.33% |
| Inception-V3 | 3 | 84.0% |
| ResNet-152 | 2 | 96.15% |
| DenseNet-201 | 2 | 96.55% |

TABLE IV
HBMCD DATA SET

| Cloud genus | Ac | As | Cc | Ci | Cs | Cu | Sc | Cb | Ns | St | sun |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Data volume | 3114 | 3047 | 3290 | 3607 | 3292 | 3526 | 3232 | 3574 | 3735 | 3791 | 4000 |
| Total volume | 38209 sheets | | | | | | | | | | |

TABLE V
DATA SET COMPARISON

| Data set | Categories | Volume | Resolving power | Categories included |
|---|---|---|---|---|
| CCSN[13] | 11 | 2543 | 400×400 | Cu、Cb、Sc、St、Ns、As、Ac、Ci、Cs、Cc、Contrail |
| HUST[12] | 6 | 1231 | 352×188 | Cu、St、Cc、Ac、As、Sun |
| SWIMCAT[11] | 5 | 1013 | 125×125 | Pattern、Thick-dark、Thick-white、Veil 、Sun |
| HBMCD | 11 | 38209 | 1358×1358 | Cu、Cb、Sc、St、Ns、As、Ac、Ci、Cs、Cc、Sun |

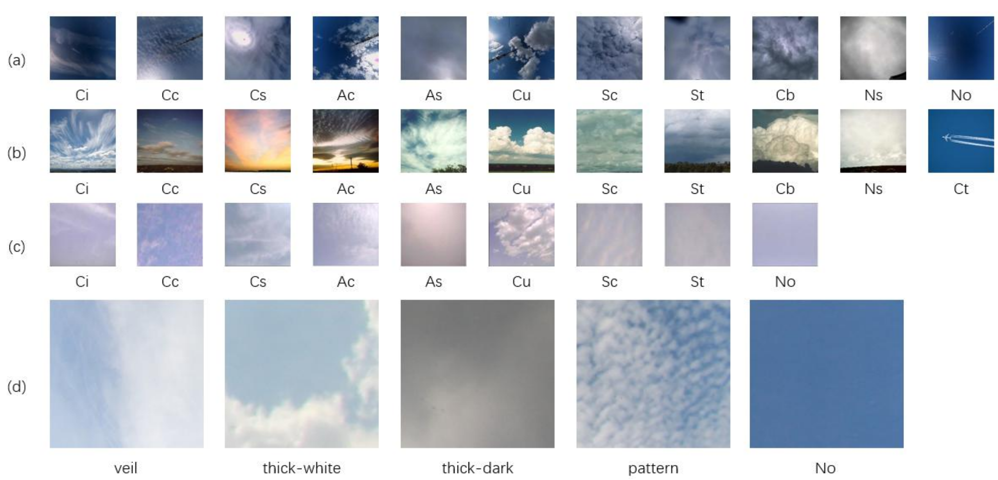


Fig.2 (a) Cloud samples from HBMCD; (b) Cloud samples from CCSN; (c)Cloud samples from HUST; (d) Cloud samples from SWIMCAT;

### *B. Feature extraction unit*

The network structure of feature extraction unit is shown in Fig.4. In this paper, four techniques are used: pointwise convolutions, depthwise convolutions (DWConv), dilated convolutions and channel shuffle [24]. First, in order to reduce the complexity of the standard convolution operation, the standard convolution is decomposed into the depthwise convolution and the pointwise convolution by using the idea of the depthwise separable convolution. This method divides the input channel and convolutes with the convolution kernel channel by channel, so theoretically reduces the size of the convolution kernel and then greatly reduces the width of the model. Pointwise convolution uses 1×1 convolution kernel for information fusion between channels and channel expansion. This method not only retains the width and depth of extracted feature units, but also greatly reduces the parameters of the model. However, in the pointwise convolutions, the dilated convolutions with different dilated rates (r = 1, 2, 3) is adopted in this paper, which makes the model have different receptive fields in the same layer, so that under the condition of effectively reducing the depth of the model, we can better extract the features of the cloud, which has a rich structure level. In addition, in the design of the network, the idea of Shortcut is used to extract the residual. Finally, in order to make full use of each channel for feature extraction, channel shuffle idea is used to make up for the loss of narrow channel width by scrambling the information between channels, so as to enhance the understanding ability of the model and reduce the boundary effect.

### *C. Downsampling unit*

The network structure of the downsampling unit is shown in Fig.5. Firstly, a pointwise convolution is used to integrate the information of the disturbed channels. Then, through 3×3 average pooling and maximum pooling, we extract the overall information and contour information of the local area, and complete the spatial scale downsampling. Then the two channels are connected and the channel width is amplified. Finally, the global pooling and two full connection layers are used to extract the overall characteristics of the connected channels, and the attention mechanism of the channel is used to multiply the output results with the original channel's feature map element by element to realize the weight distribution of the channel.

The design of feature extraction unit and downsampling unit can greatly reduce the amount of parameters and calculation in the case of small loss of accuracy. Combined with the two units, the final LCCNet network construction is formed.

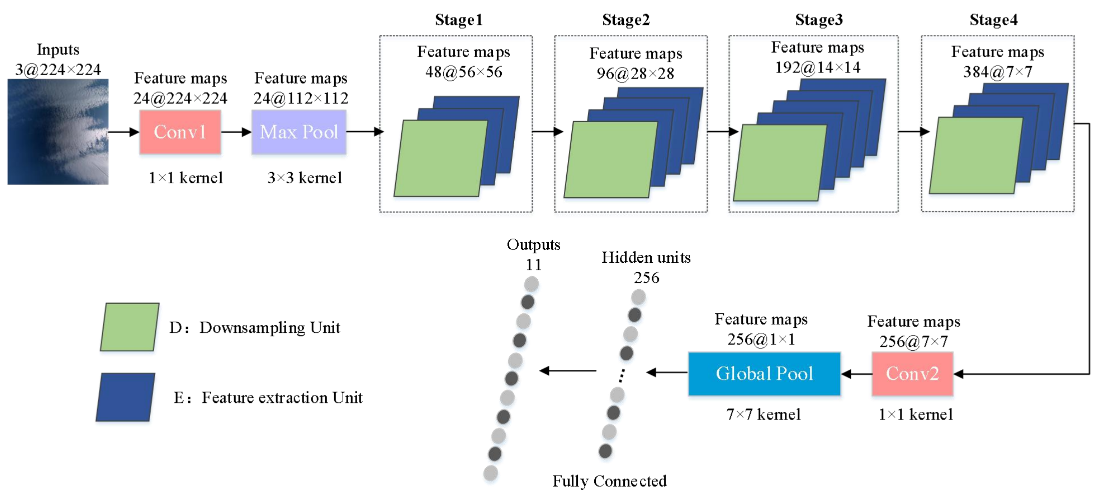


Fig.3 Cloud recognition network model——LCCNet.

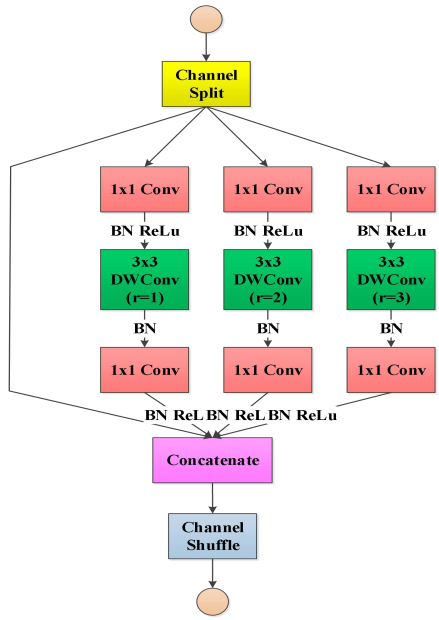


Fig.4 Feature extraction unit network model.

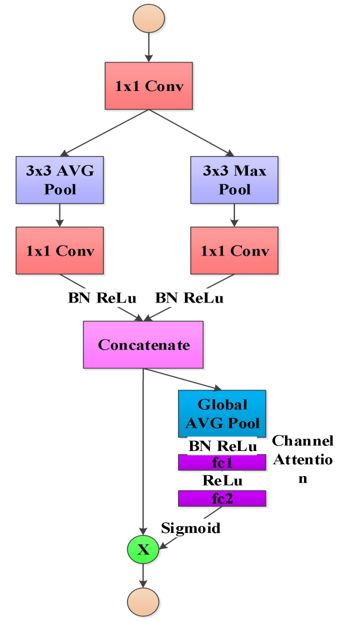


Fig.5 Downsampling unit network model.

## V. Experimental results and analysis

This section introduces the specific experimental content, including experimental configuration, visualization of model results, experimental results and analysis.

### *A. Experimental configuration*

In this paper, the HBMCD data set is divided into training set, verification set and test set in the proportion of 8:1:1 for cross validation, and the average value is obtained six times. During the training, we use the python framework to build LCCNet. The loss function is the cross entropy function. The optimizer is Adam, the batch size is set to 100, the number of iterations is set to 100, and the initial learning rate is 0.01.

### *B. Model visualization*

In this paper, Grad-Cam method is used to visualize the model results, and the visualization results are shown in Fig.6. The procedure of Grad-Cam is to select a specific target layer number for a picture, weighted average the eigenvalues of all channels of this layer number, and show the feature extraction ability of the model in the way of thermal graph. In this paper, Cirrus, Cumulus and Stratus are selected for visual display, and stage 4 is selected for specific layers of the model. As shown in Fig.6, in the Grad-Cam of Cirrus, the model pays more attention to the upper right part of the model. From the original picture, it can be observed that there are indeed standard horsetail features of Cirrus cloud in the upper right corner. In the Grad-Cam of Cumulus image, the model pays more attention to the middle left side, which is indeed the main body of the whole Cumulus in the original image. In the Grad-Cam of the Stratus cloud image, the model focuses more on the upper left part of the center. Observe the original image. Although the Stratus is almost full of the whole image, the most clear part focuses on the upper left part of the center.

Through the visualization results of these three kinds of cloud images, it is verified that LCCNet can extract the effective features of cloud images more specifically to realize the recognition of cloud shape.

### *C. Experimental result*

(1) Confusion matrix

The confusion matrix is shown in Fig.7. The abscissa is the prediction label and the ordinate is the real label. The overall experimental results of 11 categories are good, but the three categories of Cirrocumulus, Cirrostratus and Cirrus are easy to be confused. For example, 5% of Cirrostratus images are predicted to be Cirrus, and 4% of Cirrus images are predicted to be Cirrocumulus. In fact, the transformation between these three kinds of clouds is very frequent, so often an image contains two or even three kinds of clouds at the same time. In the data set, this paper determines the label of this image according to the size of a certain cloud distribution area. Therefore, when the proportions of these kinds of clouds are similar, as shown in Fig.8, the red area is Cirrostratus, the green area is Cirrus, and the blue area is Cirrocumulus. In order to make the data set more practical and reliable, these pictures are not deleted, resulting in model recognition errors.

(2) Single evaluation index

For ten kinds of cloud and one kind of cloudless cloud, this paper makes statistics on three indexes of Precision, Recall and F1-Score for a single kind of cloud, and the results are shown in Table VI. Precision, Recall, F1-Score is defined as (1)(2)(3) :

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Precision = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (3)$$

Among them, TP is true positive, which means the positive samples are correctly classified by the model; FP is false positive, which means the negative samples are incorrectly classified by the model; FN is false negative, which means the positive samples are incorrectly classified by the model. In fact, the Recall rate is the value of the diagonal position of the confusion matrix. Similar to the Recall rate, the accuracies of Cirrus, Cirrostratus and Cirrocumulus are relatively low. But on the whole, the three indicators of all kinds have reached 90%.

(3) Multiple evaluation index

In order to verify the overall performance of LCCNet, the Accuracy and Recall rate of macro and micro are calculated. The calculation formula is as follows: (4)(5)(6)(7), where $\overline{TP}$, $\overline{FP}$, $\overline{FN}$ is the arithmetic mean of 11 kinds of corresponding indexes, . It can be seen from the formula that compared with macro, micro takes into account the imbalance of data set categories.

$$P_{macro} = \frac{1}{n}\sum_{1}^{n} Precision(i) \quad (4)$$

$$P_{micro} = \frac{\overline{TP}}{\overline{TP} + \overline{FP}} \quad (5)$$

$$R_{macro} = \frac{1}{n}\sum_{1}^{n} Recall(i) \quad (6)$$

$$R_{micro} = \frac{\overline{TP}}{\overline{TP} + \overline{FN}} \quad (7)$$

As shown in Table VII, the average value of the four indexes of the model is 96.0%, which proves that LCCNet has high reliability.

(4) Comparison with other methods

This paper compares the accuracy, parameter quantity and calculation quantity with other cloud recognition models and several models commonly used in the industry. The calculation method of accuracy rate is as follows (8), where , Total is the total number of pictures:

$$Accuracy = \frac{\sum_{1}^{n}(tp(i) + tn(i))}{Total} \quad (8)$$

The experimental results are shown in Table VIII. The parameters of LCCNet are almost one-third of the current smallest network model-Shufflenet-V2, and the computational complexity is only half of it. However, the recognition accuracy is indeed the highest among all models, including other cloud recognition models and classical CNN models. It is proved that the design of LCCNet can reduce the amount and complexity of network parameters and ensure the high recognition accuracy of cloud.

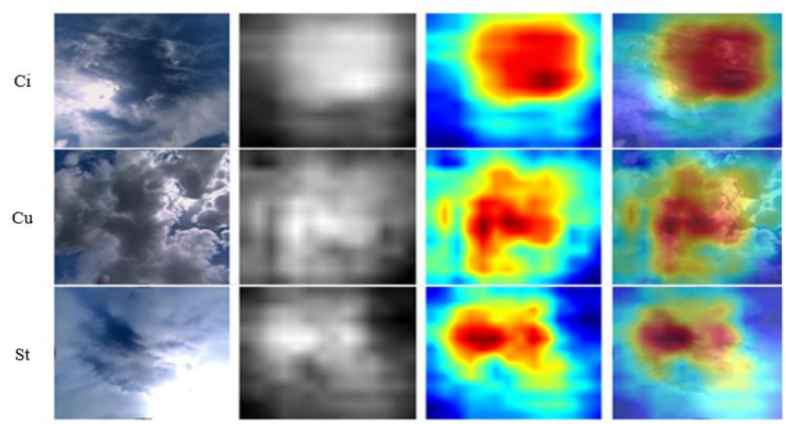


Fig.6 Feature extraction unit network model.

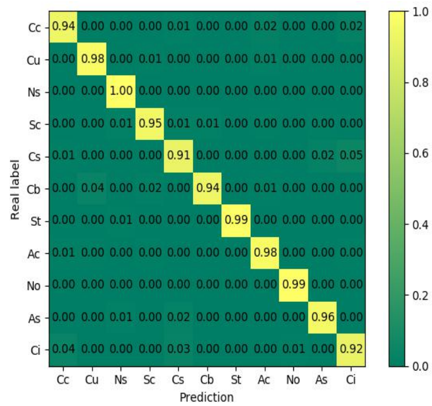


Fig.7 Confusion matrix.

Fig.8. Confusing cloud chart: the red area is Cirrostratus, the green area is Cirrus, and the blue area is Cirrocumulus.

TABLE VI
SINGLE EVALUATION INDEX

| Category | F1-Score | Precision | Recall |
|---|---|---|---|
| Cc | 92% | 90% | 94% |
| Cu | 98% | 98% | 98% |
| Ns | 97% | 95% | 100% |
| Sc | 96% | 98% | 95% |
| Cs | 92% | 92% | 91% |
| Cb | 96% | 98% | 94% |
| St | 100% | 100% | 99% |
| Ac | 97% | 95% | 98% |
| Sun | 99% | 99% | 99% |
| As | 96% | 97% | 96% |
| Ci | 92% | 93% | 92% |

TABLE VII
MULTIPLE EVALUATION INDEX

| Pmacro | Rmacro | Pmicro | Rmicro | Average |
|---|---|---|---|---|
| 95.8% | 96.1% | 96.0% | 96.0% | 96.0% |

TABLE VIII
NETWORK PERFORMANCE COMPARISON

| Network model | Accuracy | Parameter quantity | Flops / Mac |
|---|---|---|---|
| Other Cloud recognition model | | | |
| ESS[9] | 32.1% | - | - |
| CNN with TDLBP[12] | 67.1% | 30.6M | 700.1M |
| CloudNet[13] | 77.32% | 40.02M | 891.84M |
| Classical classification model | | | |
| DenseNet-201 | 96.5% | 20.01M | 4.3G |
| VGG19 | 86.1% | 19.7M | 19.67G |
| VGG16 | 91.3% | 15.5M | 15.5G |
| Inception-V3 | 93.3% | 27.16M | 2.85G |
| ResNet-152 | 95.36% | 11.58M | 11.58G |
| MobileNet-V2 | 94.02% | 2.24M | 318.97M |
| ShuffleNetV-2 | 94.35% | 1.26M | 149.58M |
| This paper | | | |
| LCCNet | 97.35% | 0.436M | 87.19M |

## VI. Conclusion

The realization of cloud precise and automatic observation has indicative significance for weather prediction, flight support and so on. It can reduce the identification error caused by the subjective factors of meteorological observers to a large extent and save human costs. In view of the problems of low data volume, incomplete types and different quality of the existing open source cloud image data sets, under the guidance of professional meteorologists, using special equipment, by means of manual annotation, transfer learning assistance and data enhancement hand, this paper constructs more than 30000 cloud image data sets covering 11 standard classes, and in terms of cloud image types, cloud image standardization and the existing disclosure The comparison of the data sets shows that the data set constructed in this paper has the advantages of large scale, full variety, high resolution and fixed angle, which lays a foundation for further research on cloud classification and counting based on the data set. Then, aiming at the problems of the existing traditional recognition algorithms, such as difficult to extract features, few recognizable cloud genera, low recognition accuracy, the existing cloud recognition methods based on deep learning need to improve the recognition accuracy, large number of parameters, and difficult to deploy, a lightweight cloud recognition network based on standard cloud image data set is proposed, This kind of network model can not only extract the features of cloud objects with rich hierarchy better, but also has a very low amount of parameters and computation, which provides the possibility for the actual deployment. Experiments show that the accuracy and fitting speed of the network model proposed in this paper are up to the advanced level in the industry. In terms of classification accuracy, this model is compared with a variety of classical models and other cloud recognition models, with the highest accuracy of 97.35%; in terms of lightweight, compared with the existing lightweight model, the parameter amount is only 1/3 of the current lightest network model, Shufflet-V2, and the calculation amount is only half of that of Shufflet-V2. A large number of experimental data verify the lightweight and high accuracy of LCCNet constructed in this paper, which can provide an effective basis for the subsequent research in weather forecast and other fields.

However, due to the small data volume of Cumulonimbus, Stratus and Nimbostratus in the current data set, it is still difficult to keep balance with other types of cloud map data even after data enhancement. It is proposed to use the network crawler technology to obtain more data in the later work, and carry out the next experiment under the condition of ensuring the data volume balance..

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