CloudNet: Ground-Based Cloud Classification With Deep Convolutional Neural Network

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Key Points:
- CloudNet is a convolutional neural network model superior to conventional ground-based cloud classification
- We propose a comprehensive ground-based cloud database consisting of 11 categories under meteorological criteria and containing three times more cloud images than the previous database
- Contrails are considered as a new type of cloud in ground-based cloud classification

Supporting Information:
- Supporting Information S1
- Figure S1

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CloudNet: Ground-Based Cloud Classification With Deep Convolutional Neural Network

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Abstract Clouds have an enormous influence on the Earth's energy balance, climate, and weather. Cloud types have different cloud radiative effects, which is an essential indicator of the cloud effect on radiation. Therefore, identifying the cloud type is important in meteorology. In this letter, we propose a new convolutional neural network model, called CloudNet, for accurate ground-based meteorological cloud classification. We build a ground-based cloud data set, called Cirrus Cumulus Stratus Nimbus, which consists of 11 categories under meteorological standards. The total number of cloud images is three times that of the previous database. In particular, it is the first time that contrails, a type of cloud generated by human activity, have been taken into account in the ground-based cloud classification, making the Cirrus Cumulus Stratus Nimbus data set more discriminative and comprehensive than existing ground-based cloud databases. The evaluation of a large number of experiments demonstrates that the proposed CloudNet model could achieve good performance in meteorological cloud classification.

Plain Language Summary With the recent progress of deep learning, an investigation is performed using convolutional neural networks (CNNs) to classify 10 typical cloud types and contrails. Although CNNs have obtained remarkable results in image classification, few works evaluate their efficiency and accuracy of cloud classification. Highly accurate and automated cloud classification approaches, especially the technology of convective cloud identification, are essential to discover a hazardous weather process. Moreover, an explicit recognition of contrails would promote the study of how the contrails impact global warming. Therefore, a discriminative and comprehensive ground-based cloud database is built for the CNNs training. The database consists of 10 categories with meteorological standards and contrails. As far as we know, it is the first time that contrails are taken into consideration as one new type of cloud in ground-based cloud classification. The total number of cloud images in our database is three times as many as that of the previously studied database. The public of this database will promote more and more research based on cloud classification. What is more, we propose the CloudNet, a new framework of CNNs, which can achieve exceeding progress compared with the conventional approaches in the ground-based cloud classification.

1. Introduction

Clouds cover more than 60% of the global surface and, consequently, play a vital role in regulating the Earth's radiation budget, through shortwave cooling and longwave warming effects (Duda et al., 2013; Rossow & Schiffer, 1991). Additionally, the cloud-type variations (e.g., variations in cloud-top height and water content) can affect both shortwave and longwave radiation. The temporal and spatial distributions of various cloud types could vary with climate change (Chen et al., 2000; Stephens, 2005). In particular, contrails have a huge effect on global climate (Minnis et al., 2005; Zhang et al., 2017). To our best knowledge, it is the first time that contrails have been taken into account in the ground-based cloud database, which makes it more valuable than existing ground-based cloud databases and will help promote the study of effects of contrails on global warming. Highly accurate automated cloud classification approaches, especially convective cloud identification, are essential to identify hazardous weather processes. The accuracy of weather prediction and rainfall estimation systems are improved substantially by having information about cloud cover distribution and being able to trace changes in meteorological conditions (Torsum & Kwiatkowska, 1999). For example, automated and immediately available interpretation of cloud images would be a powerful aid to U.S. Navy forecasters who are required to issue specialized analyses, nowcasts, and forecasts at sea (Bankert & Richard, 1994).

Ground-based cloud classification has been studied extensively in the research community over the past few decades. The conventional cloud classification method still relies on experts' experience, which makes it labor intensive. Furthermore, the task is unreliable, time-consuming, and to some extent, dependent on operator experience. The classification results usually introduce uncertainty and biases through the extraction of cloud field information from these images by visual/manual interpretation. Therefore, there is urgent demand for an automatic, accurate cloud classification method.

At present, cloud classification research is mainly based on satellite and ground observations. It is easy to obtain the large-scale global atmospheric motion status of cloud top from satellite data, although these data lack detailed local information due to the limited resolution. On the contrary, the details of local cloud cover and types are easily obtained by using ground observation instruments. With the development of continuous observation instruments, such as the whole-sky imager and the total-sky imager (Liu & Zhang, 2016; Slater et al., 2001), cloud images produced by these instruments with constant high resolution are used for cloud classification. Therefore, an increasing number of algorithms have been proposed to extract the cloud texture and structural features for cloud recognition. For instance, the local binary pattern (Ojala et al., 2000) and binary decision trees (Buch & Sun, 2005) extract features from cloud images using the texture measurement algorithm, but the accuracy of these algorithms is not sufficient. Other algorithms extract spectral features to classify seven classes of clouds and have achieved good performance (Heinle et al., 2010), but the problem of misclassification needs to be addressed. A color census transform can be used to capture texture and structure information from a color sky image simultaneously (Zhuo et al., 2014), but the overall accuracy and the number of clouds in the data set are unsatisfactory. Integrating both color and texture information has yielded excellent results in cloud taxonomies (Dev et al., 2015), but the database only has five cloud types, and the total number of clouds in the data set is 784. The learning group patterns algorithm uses wireless sensor networks to extract cloud features (Liu & Zhang, 2016), but the averaging accuracy acquired from two databases is 81%. Although these efforts have contributed to cloud classification, accurate cloud classification has not been achieved satisfactorily. Therefore, a wholly automated algorithm classifying ground-based cloud images with high accuracy is still being developed.

In the past few years, convolutional neural networks (CNNs), which are a deep learning architecture, have achieved remarkable results in some fields, such as computer vision and pattern recognition (Schroff et al., 2015; Taigman et al., 2014). CNNs can learn increasingly complex patterns and discriminative texture through large pretrained and labeled data sets, whereas it is difficult for traditional approaches to define and extract features of clouds due to the complexity of cloud texture and patterns (Lee et al., 1990). Moreover, CNNs usually function as a hierarchical feature extraction framework. In general, the shallow layers of CNNs capture the fine texture (e.g., shape and edge), and the deeper layers reflect the high-level semantic information (based on pixels). A previous study proved that both the texture and semantic features are essential for cloud characterization (Zhuo et al., 2014). Although CNNs have achieved remarkable results in image classification, few studies have evaluated their efficiency and accuracy for cloud classification. As special texture images with irregular shapes, cloud images contain distinct features in cloud representation, especially for contrails. Considering that the characteristics of clouds are highly variable and difficult to classify, the adaptive learning nature of neural network classification makes it an alternative approach to cloud classification with high accuracy and computational efficiency (Bin et al., 1999). Both the spatial layout information of fully connected (FC) features and local texture information of shallower convolutional layers are necessary from cloud representation to cloud classification.

In this letter, we present an optimized CNN model Cloud Network (CloudNet), for ground-based cloud classification. CloudNet improves the accuracy of cloud classification and avoids the mistakes caused by the conventional reliance on the empirical classification. The rest of this letter is structured as follows. We introduce the CloudNet model in section 2. Section 3 describes two data sets we used in the experiment, and the experimental detail is discussed. Section 4 gives various evaluation matrixes to assess the CloudNet model trained from the CCSN data set and compares our results with the state of art methods. Finally, the conclusions are summarized in section 5.

2. Model

2.1. Model Architecture

CloudNet, an optimized CNN, is used for the sequence-to-sequence learning task. CloudNet evolved from an improvement of Alexnet (Krizhevsky et al., 2012) and is well suited to learning features of cloud repre-

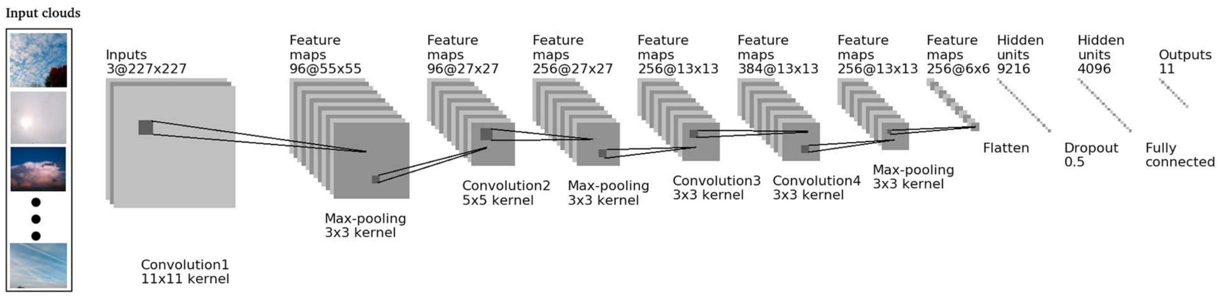

Figure 1. Illustration of the CloudNet architecture. Overall, the network contains five convolutional layers and two fully connected layers.

sentations and distinguishing the different categories of cloud images. As shown in Figure 1, the CloudNet consists of five convolutional layers and two FC layers. Thus, the architecture of CloudNet is straightforward and simple compared with previous architectures (Szegedy et al., 2015). CloudNet takes a series of fixed-size red-green-blue cloud images as inputs and a sequence of label predictions as outputs, which represent the probability of each category. In addition, to optimize the network, the input is fed into the network using a robust strategy that subtracts the mean red-green-blue value of each pixel over the training set to improve training speed and accuracy.

For such multiclass classification problems, directly applying the FC layers and convolutional layers of a CNN cannot give satisfactory results (Shi et al., 2017; Ye et al., 2017). Because the cloud feature is hard to extract, the third and fourth convolutional layers are connected directly without a pooling layer. We apply dropout (Srivastava et al., 2014) to the fifth and sixth FC layer after the nonlinearity. The final layer of softmax activation produces a distribution over the 11 output probability classes for each category. We use the stochastic gradient descent (Tsuruoka et al., 2009) optimizer with the default parameters (Krizhevsky et al., 2012) in the experiment. CloudNet is trained from scratch. Finally, we save the best model configuration, as evaluated with a test set during the optimization process.

3. Data

3.1. Ground-Based Cloud Databases

To train any neural network that requires supervised learning to do classification work, expertly labeled data must be available. The availability of sufficient training samples is the fundamental issue that should be addressed (Xiao et al., 2016; Zhuo et al., 2014). In addition, creating a more extensive database for training and testing contributes greatly to the accuracy of classification (Bankert & Richard, 1994). Therefore, to achieve high performance, the scale of the labeled data sets is the critical factor in allowing CNNs to work efficiently. For example, the ImageNet (Deng et al., 2014) consists of over 10 million labeled images and is the most well-known and comprehensive data set and is suitable for different kinds of image classification methods.

1. Singapore Whole-sky Imaging Categories (SWIMCAT) Data set: the SWIMCAT database (Dev et al., 2015), contains 784 sky/cloud patch images with 125 × 125 pixels. The data sets are divided into five distinct categories: clear sky, patterned clouds, thick dark clouds, thick white clouds, and veil clouds. Some representative samples of the five categories clouds are shown in Figure 2c. There are several studies (Dev et al., 2015; Shi et al., 2017) based on the SWIMCAT data set, but the data set does not include all the required cloud categories, which is insufficient from the perspective of meteorological research and applications.
2. Cirrus Cumulus Stratus Nimbus (CCSN) Data set: we construct a CCSN data set under the meteorological criteria. The data set is three times larger than SWIMCAT and contains 2,543 unique ground-based cloud images, which are labeled after several rounds of subjective classification based on visual characteristics and meteorological experts' experience. According to the World Meteorological Organization's genera-based classification recommendation, we divide CCSN into 10 categories. Contrails are added as a new category to the CCSN data set. The total number of samples increases the training difficulty but improves the feature extraction of CloudNet trained with the CCSN data set. Moreover, due to the large number of cloud types, cloud images in this database have large illumination variation and intraclass variation. In the CCSN data sets, all images have a resolution of 256 × 256 and are in the JPEG format. Table 1 presents the descrip-

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Figure 2. Cloud samples from (a; left to right) the CCSN database followed by Ac, Sc, Ns, Cu, Ci, Cc, Cb, As, Ct, Cs, St, (b) the six-class HUST (Huazhong University of Science and Technology) database (Zhuo et al., 2014) followed by Ac, As, Cc, Clear sky, Cs, Cu, Sc, St and Ci, and (c) clouds images come from SWIMCAT (Dev et al., 2015) followed by Clear sky, patterned clouds, thick dark clouds, thick white clouds and veil clouds. CCSN = Cirrus Cumulus Stratus Nimbus; SWIMCAT = Singapore Whole-sky Imaging Categories; Ci = cirrus; Cs = cirrostratus; Cc = cirrocumulus; Ac = altocumulus; As = altostratus; Cu = cumulus; Cb = cumulonimbus; Ns = nimbostratus; Sc = stratocumulus; St = stratus; Ct = contrail.

tions of the cloud categories in the CCSN database. Figure 2a shows some cloud samples in the CCSN data set. Compared with the enormous number of samples in the ImageNet data set (Deng et al., 2014), the number of training samples in the CCSN data set is small. However, the three databases in Figures 2a–2c show that our database measures classification accuracy better than the other two databases, which are less representative, implying that our CCSN database is superior to other databases.

3.2. Implementation Illustrations

All kinds of clouds possess an abundance of textures, which can be used to describe the appearance of the cloud. For one individual convolutional layer, the different filter banks are used to capture textures like edges, spots, and bars. Each filter is trained to obtain a high response for a given pattern or texture (Ye et al., 2017). The visualization of each layer of CloudNet can be found in Figure 3, in which we just show one of the numerous units produced by the convolutional operation on each layer. The feature maps of the convolutional layers present different activation effects for the same cloud image. Figures 3a, 3c, and 3e show the visualization of feature maps in different convolutional layers, whereas Figures 3b, 3d, and 3f show the reconstruction of the cloud image using the corresponding features. Analyzed with feature maps and reconstruction cloud images,

Table 1
Details of Cirrus Cumulus Stratus Nimbus Database

Category	Number of images	Type	Description
Ci	139	Cirrus	Fibrous, white feathery clouds of ice crystals
Cs	287	Cirrostratus	Milky, translucent cloud veil of ice crystals
Cc	268	Cirrocumulus	Fleecy cloud, cloud banks of small, white flakes
Ac	221	Altocumulus	Grey cloud bundles, compound like rough fleecy cloud
As	188	Altostratus	Dense, gray layer cloud, often even and opaque
Cu	182	Cumulus	Heap clouds with flat bases in the middle or lower level
Cb	242	Cumulonimbus	Middle or lower cloud level thundercloud
Ns	274	Nimbostratus	Rain cloud; grey, dark layer cloud, indistinct outlines
Sc	340	Stratocumulus	Rollers or banks of compound dark gray layer cloud
St	202	Stratus	Low layer cloud, causes fog or fine precipitation
Ct	200	Contrails	Line-shaped clouds produced by aircraft engine exhausts
Total	2,543		

Note. The generic name of the cloud abbreviation is used to represent the category.

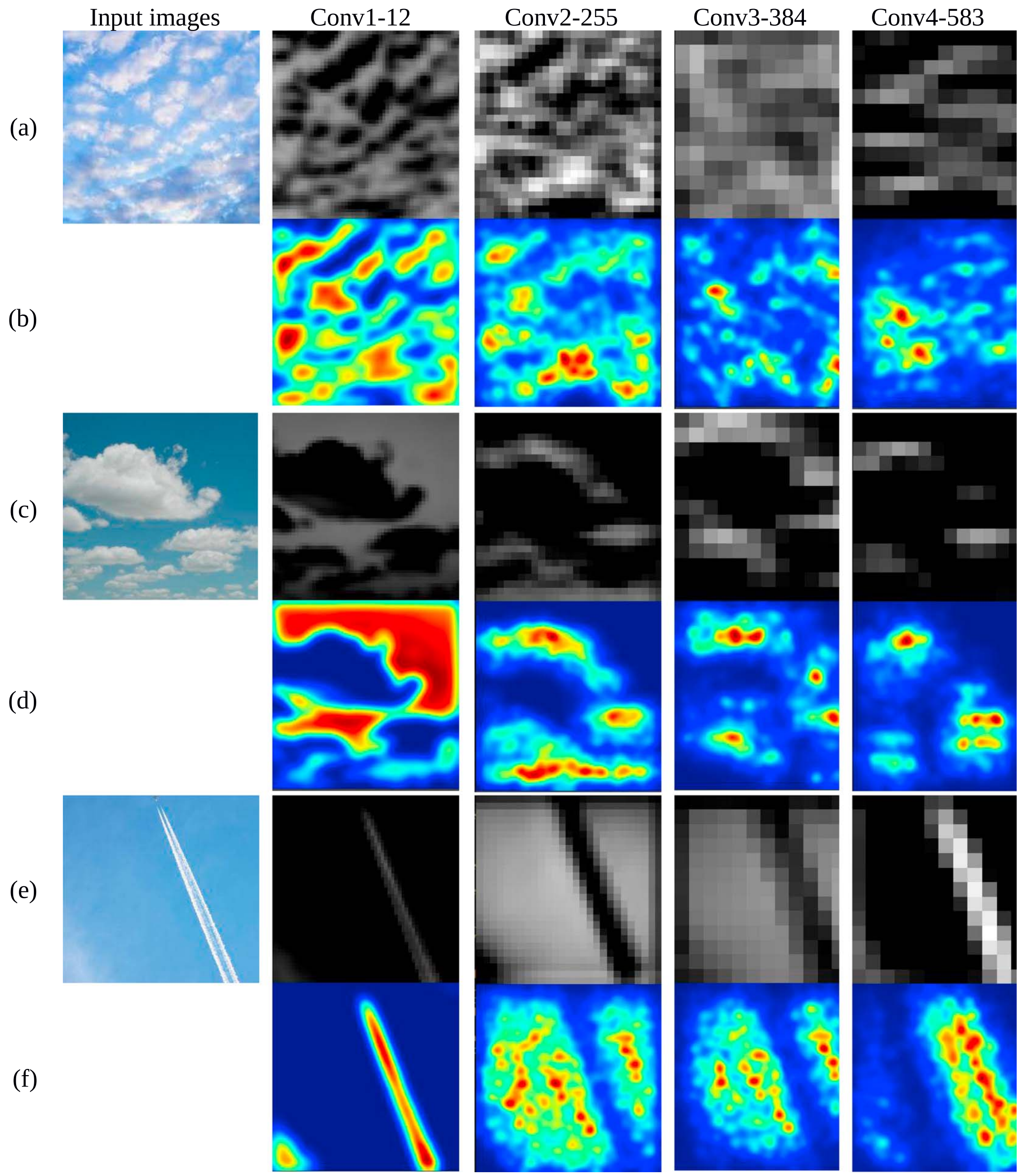


Figure 3. (a, c, and e) Visualization of features from four convolutional layers of CloudNet, denoted Conv1-12 (channel number 12 on Conv1), Conv2-255, Conv3-384, and Conv4-583. The corresponding reconstructions of the cloud images are shown in (b), (d), and (f) visualized via regularized optimization.

the first layer (shallow layer like Conv1) of CloudNet can well reflect the shape of different clouds. Furthermore, the deep layer (Conv2, Conv3, and Conv4) can recover the edges of different clouds well.

For both the SWIMCAT and CCSN data sets, the samples are divided into a training set and a test set. First, we verify the data set to make sure that there is no cloud image overlap between the training and test set. Before the CloudNet training, we subtract the mean activity over the training set for each pixel and adopt data augmentation methods, such as random crop and flip, to increase the number of training samples. Moreover, the model trained from this data set shows excellent generalization, which prevents overfitting during training and makes the model more efficient and robust. CloudNet is trained with a stochastic gradient using the machine learning software package Caffe (Jia et al., 2014) and running on an NVIDIA GeForce GTX780Ti with batch size 8. Our experiments use momentum parameters (Sutskever et al., 2013) with a decay of 0.9. In addition, we use a learning rate of 0.001 and train 20,000 epochs. The learning rate is reduced by a factor of 10 every 5,000 epochs.

Table 2
Performance Evaluation of C ategories in the Cirrus Cumulus Stratus Nimbus Database

Category	F measures	Precision	Recall	Accuracy
Ci	0.96	0.92	1	0.89
Cs	0.76	0.89	0.67	0.86
Cc	0.96	0.92	1	0.89
Ac	0.96	0.92	1	0.89
As	0.59	1	0.42	0.86
Cu	0.96	0.92	1	0.89
Cb	0.92	0.92	0.92	0.88
Ns	0.96	1	0.92	0.89
Sc	0.69	0.52	1	0.83
St	0.82	0.9	0.75	0.87
Ct	1	1	1	0.9

Note. Ci = cirrus; Cs = cirrostratus; Cc = cirrocumulus; Ac = altocumulus; As = altostratus; Cu = cumulus; Cb = cumulonimbus; Ns = nimbostratus; Sc = stratocumulus; St = stratus; Ct = contrail.

4. Experimental Results and Analysis

4.1. Experimental Configuration

To evaluate the CloudNet model objectively, the CloudNet configuration was trained from the CCSN data set and SWIMCAT database as the pre-trained model. The individual classification precision, recall, F measures, and accuracy are evaluated for the 11 categories in the CCSN data set. Precision refers to the proportion of relevant instances among the retrieved instances, whereas recall or sensitivity refers to the percentage of appropriate instances that have been retrieved over the total amount of relevant instances. Therefore, both precision and recall used here are based on a comprehensive understanding and the effectiveness measurement of our model. F measure considers both accuracy and precision and can be interpreted as a weighted harmonic mean of the precision and recall. We also report the macroprecision and microprecision. In such a multiclass classification task, macroprecision gives equal weight to each cloud class. Therefore, it is an indication of CloudNet performance across all the cloud categories. However, microprecision gives equal weight to each per-type classification decision (Dev et al., 2015; Sebastiani, 2002).

The calculations (Asch, 2013) are as follows. True positives (tp), true negatives (tn), false positives (fp), and false negatives (fn) are used to calculate precision, recall, and accuracy.

$$\text{Precision} = \frac{tp}{tp+fp}, \text{Recall} = \frac{tp}{tp+fn}, \text{Accuracy} = \frac{\sum_c^C tp_c}{N}, \tag{1}$$

where tp_c is the number of tp for class c, C is the number of classes, and N is the total number of instances in the data set.

$$F - \text{score}(\beta) = \frac{(1+\beta^2)tp}{(1+\beta^2)tp+\beta^2 fp+fn}. \tag{2}$$

Most commonly, β is taken to be 1, with a definition equal to the F measure. F_β measure reaches its best value at 1 and its worst score at 0. The macroaveraged results can be computed as

$$B_{\text{macro}} = \frac{1}{q}\sum_{\lambda=1}^{q} B(tp_\lambda, fp_\lambda, tp_\lambda, fn_\lambda), \tag{3}$$

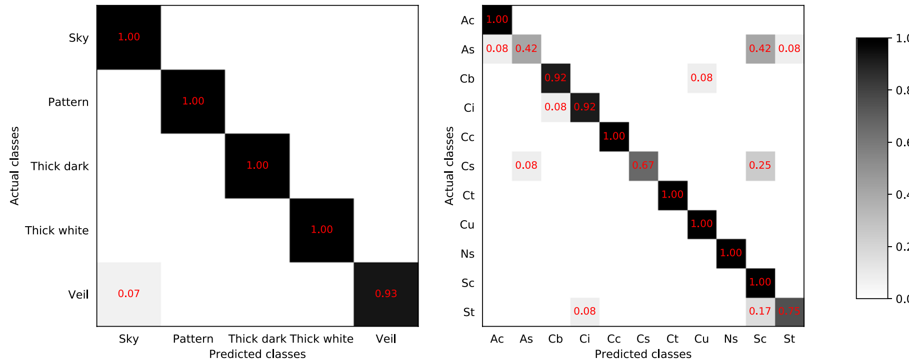
whereas the microaveraged can be computed as

$$B_{\text{micro}} = B\left(\sum_{\lambda=1}^{q} tp_\lambda, \sum_{\lambda=1}^{q} fp_\lambda, \sum_{\lambda=1}^{q} tp_\lambda, \sum_{\lambda=1}^{q} fn_\lambda\right). \tag{4}$$

The $L = \lambda_j, (j=1 \ \ldots\ q)$ is the set of labels, whereas $B(tp, tn, fp, fn)$ is calculated based on the number of tp, tn, fp, and fn, respectively. Let tp_λ, fp_λ, tn_λ, and fn_λ represent the number of tp, fp, tn, and fn after binary evaluation for a label λ.

Table 3
Performance Evaluation Measures for the Cirrus Cumulus Stratus Nimbus Database

$\mathbf{P}_{\text{macro}}$	$\mathbf{R}_{\text{macro}}$	$\mathbf{P}_{\text{micro}}$	$\mathbf{R}_{\text{micro}}$	Average
0.91	0.87	0.87	0.87	0.88



(a) (b)

Figure 4. Two confusion matrices are used to evaluate the effectiveness of CloudNet. Confusion matrix (a) is the model prediction with the Singapore Whole-sky Imaging Categories test set, which randomly selects 12 images in each category. Confusion matrix (b) is the same as (a), but (b) is the model prediction with the Cirrus Cumulus Stratus Nimbus test set. Ci = cirrus; Cs = cirrostratus; Cc = cirrocumulus; Ac = altocumulus; As = altostratus; Cu = cumulus; Cb = cumulonimbus; Ns = nimbostratus; Sc = stratocumulus; St = stratus; Ct = contrail.

4.2. Results Discussion

Tables 2 and 3 show the performance assessment of cloud classification of the CCSN database using different evaluation matrices for each category. Sc in Table 2 has a poor precision of 52% but a high recall of 100%, and As has a recall of 42% but a high precision 100%. Most of the remaining cloud classes show accuracies ranging from 86% to 96%. Therefore, our proposed classification approach achieves near-perfect classification accuracy for most categories. Table 3 displays the experimental classification results, giving overall score rates ranging from 87% to 91%, which are superior to the state-of-the-art methods (Xiao et al., 2016; Ye et al., 2017) with average scores of 81% and 87%, respectively. Moreover, the average score is 88%, which indicates the effectiveness and generalization of CloudNet. Because of the critical and comprehensive database we built and the unique model we used, the experimental results are rather good.

Figure 4a illustrates the confusion matrix of prediction maps with the SWIMCAT test data set. The misclassification of the veil background and clear sky causes the poor performance of veil category. However, the overall classification accuracy of CloudNet still outperforms the other traditional classification methods. For example, confusion occurred between thick dark clouds and veil cloud in Dev et al. (2015), and their experimental results of 0.02 and 0.15 are higher than our results. Figure 4b shows a confusion matrix of CloudNet predictions with the CCSN test data set. A small number of incorrect classifications are close to the correct classes in both morphological and meteorological criterion. For example, confusing As and Sc seems to make sense, due to the highly similar shape, structure, transparency, and arrangement of the two categories. The height is the main difference between the categories; As is a high type of clouds, whereas Sc is a low type of cloud.

5. Conclusion

Based on recent progress in deep learning, we used CNNs to classify 10 typical cloud types and contrails. Automated ground-based cloud classification would be a valuable tool in meteorological analyses and forecasting and could build an accurate connection between cloud types and radiative properties for climate change predictions. We proposed a deep learning model, CloudNet, for ground-based cloud classification, relying on texture, structure, and shape features simultaneously. We also built a large, annotated CCSN data set that maps a sequence of raw cloud images with ground truth labels. We also considered contrails for the first time in the CCSN data set.

Extensive experimental results indicate that the CloudNet achieves high efficiency with the online SWIMCAT data set and performs well with the complicated CCSN data set in the ground-based cloud classification challenge. A small portion of the misclassifications occurred between As and Sc, Cs and Sc, and Sc and St. These errors, however, are well understood. There is a mutual transformation among the three types of clouds. Introducing features from other data sources to enrich the CCSN database may improve the classification accuracy. Furthermore, we confirmed that better results could be obtained with abundant information about the different location and cross-domain effects, such as local illumination conditions. We are convinced that the algorithm can be improved by using the instructions clarified above to eliminate errors caused by questionable images. However, the CNN presented here is already robust and suitable for research purposes.

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