Cloud Classification of Ground-based Cloud Images based on Convolutional Neural Network

Tingting Zhu1,2*, Liang Wei1 and Yiren Guo1

1 College of Mechanical and Electronic Engineering, Nanjing Forestry University, Nanjing 210037, China;
2 Key Laboratory of Measurement and Control of Complex Systems of Engineering (Southeast University), Ministry of Education, Nanjing 210096, China
*Corresponding author’s e-mail: tingtingzhu@njfu.edu.cn

Abstract. Cloud is a crucial meteorological factor, and also a key factor affecting solar radiation variables for solar energy, especially the attenuation of different cloud types on solar radiation. However, there are few researches on the cloud classification based on the ground-based cloud image in order to predict solar energy. In this paper, the ground-based cloud images were collected, and then they were classified into five classes based on colour, texture and the attenuation on the theoretical clear-sky solar radiation. The ResNet18 model was trained to classify the ground-based cloud images automatically. The experimental results show that the classification accuracy of the ResNet18 is up to 91%, which is higher than the other two convolutional neural networks (AlexNet and VGG16) and is also much higher than the traditional machine learning classifiers. This work provides a new perspective and important supporting data for solar radiation forecast.

1. Introduction

With the depletion of fossil energy and the increasingly serious global environmental pollution and climate changes, renewable energy is being developed all over the world, such as wind energy and solar energy [1]. However, solar energy is intermittent and fluctuant. Its uncertainty would endanger the safety of power grid without accuracy prediction when integrating into power grid [2]. Therefore, the accurate forecast of solar energy power is very important and necessary [3].

Cloud is a crucial meteorological factor, and also a key factor affecting solar radiation variables. However, the major of researches focus on the influence of cloud cover on solar radiation, while ignore the effect of different types of cloud [4,5]. In factor, the cloud type is more important for solar radiation than cloud cover [6,7]. In addition, the observation scale of a ground-based cloud image is more suitable than satellite image for a photovoltaic power station [8].

Currently, there are some published works on cloud classification using traditional machine learning methods, such as Support Vector Machine (SVM), Naive Bayes, and K-Nearest Neighbour (KNN), and these methods are all based on features extracted manually by researchers [9,10]. The classification accuracy of these methods are dependent on the manual features. However, it is different for manual features to describe exactly the boundary between cloud and sky, especially for cirrus or stratus, and it is also different to describe the interior changes within cloud. Therefore, the deep learning methods were tried to be used to classify clouds taking their advantage of extracting feature automatically.
In this paper, a classification of cloud was developed based on not only the colour and texture characters of cloud but also attenuation of solar radiation. Meanwhile, a convolutional neural network model was used to classify the ground-based cloud images and achieved a satisfactory classification results, which is better than the traditional machine learning methods.

2. Materials and Method

2.1. Data collection

The ground-based cloud images were taken by the total sky imager (TSI-880), which were all downloaded from the National Renewable Energy Laboratory’s Solar Radiation Research Laboratory (SSRL) [11]. The ground-based cloud images were classified into five types according to the colour and texture characters of cloud but ignoring cloud base height. Each type consists of 100 samples and 500 ground-based cloud images were collected in total as a training set from the year of 2013. Another 500 ground-based cloud images were collected from the year of 2014 as a testing set. Figure 1 shows five samples of each type of the cloud, where the type of nimbus includes cumulonimbus and nimbostratus. Figure 2 shows the attenuation of every type of clouds on solar radiation compared with the theoretical value of the clear sky solar radiation [12].

![Figure 1. Five types of cloud samples ignoring cloud base height.](image1)

![Figure 2. Attenuation of every type of clouds on solar radiation.](image2)

2.2. Cloud classification based on CNN

The convolutional neural networks (CNNs) are able to extract the features of images automatically, which makes it easy for images to be studied [13]. The typical structure of the CNN includes:

- Convolutional layer, a set of convolutional filters that activate image features;
• Rectified linear unit layer, an activation function;
• Pooling layer, a form of down sampling;
• Fully connected layer, which integrates the features extracted from the previous layers and outputs them to one dimension;
• Softmax layer, which gives the probability of each category established in the database when classification starts.

In this work, the ResNet18 [14] was selected to classify the ground-based cloud image because of its compensation between depth and performance.

2.2.1 The structure of the classification model
The ResNet18 consists of 17 convolutional layers, 2 pooling layers (Maximum and average), and 1 fully connected layer with a softmax. Its structure is shown as Figure 3. A RGB ground-based cloud image (3×352×288) was transformed into 3×224×224 as input of ResNet18.

![Figure 3. The structure of ResNet18, where 17 convolutional layers (conv) and 1 fully connected layer (FC) constitute the 18 layers in the network name.](image)

2.2.2 The optimizer of the classification model
Usually, the Stochastic Gradient descent method [15] and Adaptive Moment Estimation (Adam) [16] method were used to calculate the parameters of ResNet18 model. The main process could be concluded as the following three steps:

Step 1: calculate the gradient of every current parameter in the cost function, as:
\[ g_t = \nabla f (w_t) \]  (1)

Step 2: calculate the adjustment values of the current parameter;
\[ \eta_t = \alpha \cdot g_t \]  (2)

Step 3: update the parameters of ResNet18, as:
\[ w_{t+1} = w_t - \eta_t \]  (3)
The most difference between the SGD and the Adam is in the Step 2, and the details have been described in reference [16].

3. Results and Discussions

In this section, there are three groups of experiments carried out to evaluated the cloud classification by the ResNet18. All experiments were carried out on the following hardware platforms: Intel Core i7-8700 CPU@3.2GHz, with 32GB memory and an NVIDIA GeForce RTX 2080 Ti (11G memory) video card.

3.1. Classification accuracy of CNN with different optimizers

The first group of experiments were to access the rationality of network selection and optimizer, and the results are listed in Table 2, where the AlexNet [17] consists of 5 convolutional layers and 3 fully connected layers, and the VGG16 [18] is with 13 convolutional layers and 3 fully connected layers. The performance of the ResNet18 is best among the three deep learning methods, which means that the increasing of network layer number could improve the classification accuracy. By comparing the two optimizers, the CNN models with the Adam method could achieve higher classification accuracy.

Table 1. Classification accuracy of CNN with different optimizers.

| Optimizers | AlexNet [16] | VGG16 [17] | ResNet18 |
|------------|--------------|------------|----------|
| Adam       | 82%          | 85%        | 91%      |
| SGD        | 67%          | 77%        | 83%      |

3.2. Classification accuracy of different methods

The second group of experiments were to analyse the performance of different method including traditional machine learning methods (SVM, Naïve Bayes and KNN) and the deep learning methods, and the results are shown as in Figure 4. It is clear that the deep learning methods do better than the traditional machine learning methods. That is because the manual extracted features cannot describe precisely the different characteristic of each cloud.

![Figure 4. Classification accuracy of different methods for the testing set.](image)

3.3. Classification accuracy for different types of clouds

To further illustrate the classification performance of the ResNet18 model, the classification results of each type are listed in Table 2. The classification of clear-sky is the most accurate and reaches up to 98%, followed by Nimbus (96%). The type of cirrus is detected worst, which is classified mistakenly into clear-sky (7%) or stratus (10%). When the cloud cover is very small in the whole sky, the cirrus cloud is easily classified mistakenly into clear-sky. For the other thing, the cirrus cloud is easily
classified mistakenly into the stratus cloud, when the cloud cover is more than 0.5 and the cirrus is transforming into the stratus.

Table 2. Confusion matrix of ResNet18 for cloud classification.

| Classified | True classes |
|------------|--------------|
| Cirrus     | 82  7  1   0  10 |
| Clear-sky  | 1   98  1   0  0  |
| Cumulus    | 3   2   88  2  5  |
| Nimbus     | 0   0   1   96 3  |
| Stratus    | 7   0   1   1  91 |

4. Conclusion
This paper proposed a new cloud classification principle not only based on the colour and texture of cloud but also the attenuation of cloud on solar radiation, which the classification results will be of great help to the improvement of solar radiation predicting accuracy. What’s more, the different methods were carried out to classify the ground-based cloud images. The experimental results show that the ResNet18 does the best among all the tested models, and its classification accuracy is up to 91% with the Adam optimizer, and that the deep learning methods are all better than the traditional machine learning methods.

In this work, the classification accuracy of the cirrus cloud is lower than the other four types of clouds, but the mistaken cloud has the similar attenuation on solar radiation as the classified type. Therefore, the mistaken classification may have little effect on the solar radiation forecast. In future, we will focus on solar radiation forecast or solar energy forecast based on cloud classification.

Acknowledgments
The authors acknowledge the National Renewable Energy Laboratory for providing the data used in this paper. This research was funded by the National Natural Science Program of China, grant number 62006120, and the Key Laboratory of Measurement and Control of Complex Systems of Engineering (Southeast University), Ministry of Education, grant number MCCSE2020A02.

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