CLOUD TYPE CLASSIFICATION IN GROUND-BASED SKY IMAGES WITH DEEP LEARNING

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Abstract

Clouds cover more than half of the Earth's surface and are the subject of intense research in climate modeling, weather forecasting, meteorology, solar energy research, and satellite communications. Determination of cloud types and characteristics is of great importance in developing and applying solar radiation forecasting models. Therefore, classifying clouds into different categories according to their optical properties is essential for developing solar radiation forecasting algorithms. In this study, we have tried to develop a more efficient, reliable, and cost-effective solution for cloud classification. In this context, a deep-learning CNN model that can classify six different cloud types is developed, and its performance and applicability are examined. The SWIMCAT-EXT dataset, available for research activities, is used for training and testing the model. The experimental results show that the proposed CNN model can successfully classify cloud types and can be integrated into the solar radiation forecasting process.

Keywords: C*loud classification, convolutional neural network (cnn), deep learning, solar irradiance prediction*

1. INTRODUCTION

Clouds, which are widespread phenomena in the atmosphere, cover a considerable expanse of the Earth's surface and comprise water vapor and ice crystals. Due to their effects on solar radiation, including its reflection, absorption, and obstruction, they have become a subject of extensive investigation in diverse academic fields concerning solar energy, atmospheric conditions, and weather forecasts. Cloud properties analysis is particularly crucial, with cloud classification playing a pivotal role in this context. The accurate identification of cloud types and their characteristics is vital for the development and implementation of solar radiation forecasting models. The modification of solar radiation by clouds depends on various factors, including the size, shape, and composition of water droplets or ice crystals. Proper cloud classification based on their optical properties is indispensable for devising reliable solar radiation forecasting algorithms. Utilizing precise cloud classification data can lead to more accurate forecasting models that take into account the intricate effects of clouds on solar radiation.

Presently, cloud type classification is mainly conducted by professional observers, a process that is both time-consuming and prone to errors, omissions, and other inaccuracies, potentially impacting the validity of data. Consequently, there is an increasing demand for automatic cloud classification techniques. In recent studies focusing on this field, notable progress has been achieved, primarily categorized into two types: classical methods rooted in machine learning and advanced methods based on deep learning. For instance, Gan et al. introduced an innovative duplex norm-bounded sparse coding algorithm to classify cloud types. Their approach involves capturing comprehensive features from cloud images to construct a holistic representation (Gan et al. 2017). Luo et al. introduced a method based on combining manifold and texture features of clouds from ground-based infrared images, proving its effectiveness (Luo et al. 2018). Additionally, Luo et al. presented a cloud classification method using ground-based imagery and a combination of Manifold Kernel Sparse Coding and Dictionary Learning algorithms, achieving successful results (Luo, Zhou & Meng). Wang et al. employed stable local binary patterns (SLBP) for feature detection and cloud classification, demonstrating its potential utility (Wang et al. 2018). Deep learning approaches have also garnered attention and shown promising performances. Zhang et al. proposed a method employing deep visual information transfer (DVIT) to recognize cloud types using multiple ground-based images (Zhang, Li, et al. 2018). Phung and Rhee designed a CNN model specifically for classifying cloud types and handling small datasets (Phung & Rhee 2018). Zhang et al. presented a CNN-based cloud classification method utilizing the CloudNet model to identify cloud features from cloud images and classify them successfully (Zhang, Liu, et al. 2018).

This study endeavors to develop a more efficient, reliable, and cost-effective solution for cloud classification. A deep learning model capable of classifying six distinct cloud types is created and evaluated for its performance and applicability. The SWIMCAT-EXT dataset (Dev, Lee & Winkler 2015) is employed for training and testing the model. The subsequent sections of this article elaborate on the dataset and the CNN deep learning model developed. Additionally, experimental studies and the obtained results are discussed in the third section, followed by a summary of conclusions in the fourth section.

2. MATERIALS AND METHODS

2.1. Data Set Used (SWIMCAT-EXT)

In the realm of cloud classification research, the availability of comprehensive datasets remains relatively scarce. A prominent dataset utilized in recent investigations, as described by Dev et al. (2015), is the Singapore Whole-Sky Imaging categories (SWIMCAT) database. This dataset is widely recognized and embraced in the field. The core content of SWIMCAT comprises sky images gathered in Singapore, employing a sophisticated wide-angle, high-resolution sky imaging system (WAHRSIS) alongside meticulously calibrated whole-sky imagers.

The SWIMCAT dataset encompasses five distinct cloud types, namely: clear skies, patterned clouds, thick black clouds, thick white clouds, and veil clouds. These classifications are determined by a meticulous assessment of the visual characteristics related to atmospheric phenomena, which includes seeking guidance from knowledgeable experts affiliated with the esteemed meteorological services of Singapore (Dev, Lee & Winkler 2015). To enhance the comprehensiveness and applicability of our study, we leveraged the SWIMCAT-EXT dataset, an extension of the original SWIMCAT database. Additionally curated and assembled by Truong Hoang and Vinh (Truong Hoang & Vinh 2020), this extended dataset includes an additional cloud class, namely, thin white clouds. This augmentation ensures a more exhaustive representation of cloud variability. The SWIMCAT-EXT dataset comprises a total of 350 images for each cloud class, meticulously curated to provide a balanced distribution across the distinct categories. Each image boasts a resolution of 125x125 pixels, guaranteeing a robust foundation for our investigation.

In Figure 1, we present a selection of random images showcasing the six cloud classes contained within the SWIMCAT-EXT dataset. These images offer a glimpse into the visual diversity and complexity of cloud formations, enabling a detailed analysis and classification in our research endeavors.

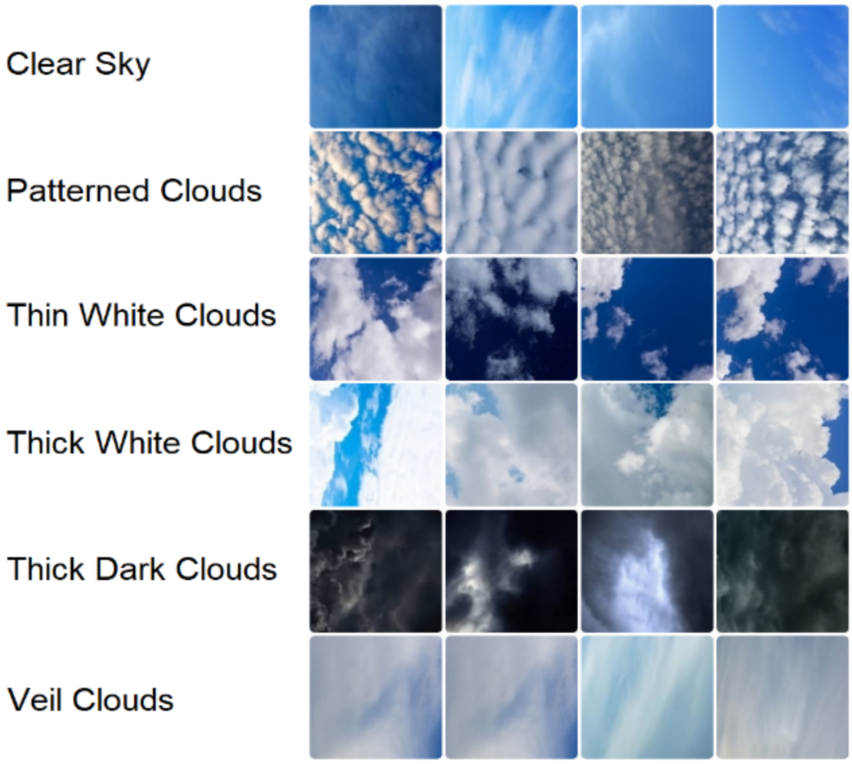

Figure 1. Some random images of six different cloud classes in the SWIMCAT-EXT dataset

2.2. Creating the CNN Model

CNNs are deep learning networks now widely used for visual classification, focusing on pattern recognition, object detection, and other visual processing (Phung & Rhee 2018). Unlike other pattern recognition algorithms, CNNs can perform feature extraction and classification. A simple CNN architecture consists of five layers. An example of the relevant CNN architecture is presented in Figure 2 (Phung & Rhee 2018).

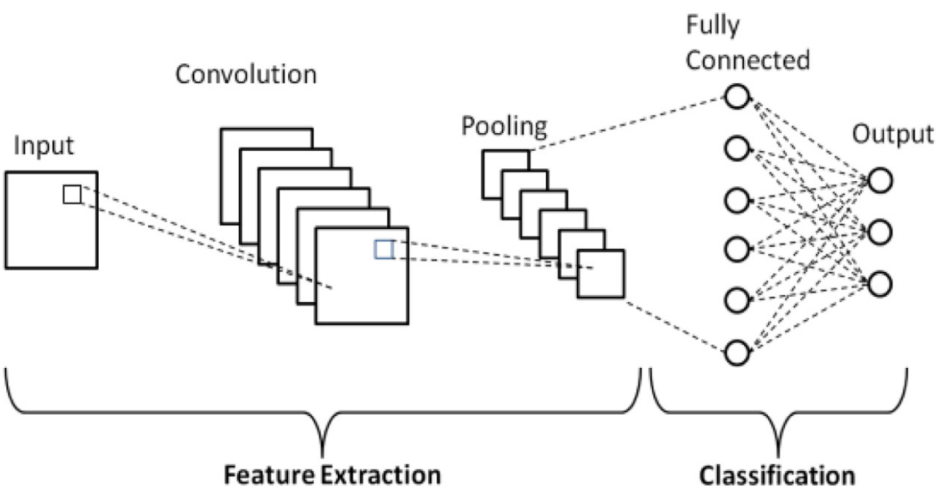

Figure 2. An example of a simple CNN architecture

Source: Phung, VH & Rhee, EJ 2018, 'A deep learning approach for classification of cloud image patches on small datasets', Journal of information and communication convergence engineering, vol. 16, no. 3, pp. 173-178.

In Figure 2, a basic CNN architecture is illustrated, comprising five distinct layers: the input layer, the convolution layer, the pooling layer, the fully connected layer (FC layer), and the output layer. The initial three layers are dedicated to feature extraction, while the last two serve for classification purposes. The input layer sets a consistent scale for the input images, regulating their dimensions accordingly. The convolution layer plays a pivotal role in feature extraction by employing learned filters (kernels) of a specific size to convolve over the image, thereby identifying and consolidating key features. Consequently, it facilitates the extraction of meaningful information from the image. The pooling layer generates feature maps that retain content while reducing image dimensions, resulting in a decrease in computational load. The fully connected layers merge the features extracted in the preceding layers, building a larger and more intricate model. In the output layer, multiple neurons represent the categories of individual objects. Ultimately, this layer analyzes the aggregated features from the fully connected layers to predict the classification of objects present in the input image. For the cloud classification problem addressed in our study, the CNN model's architecture is presented in Table 1.

Layer	Shape	Filter Shape	Window Shape	Dropout Rate
Input	125 * 125 * 3	-	-	-
Conv.1	125 * 125 * 256	3 * 3	-	-
Relu	125 * 125 * 256	-	-	-
Pooling	62 * 62 * 256	-	2 * 2	-
Conv.2	62 * 62 * 128	3 * 3	-	-
Relu	62 * 62 * 128	-	-	-
Pooling	31 * 31 * 128	-	2 * 2	-
Conv.3	31 * 31 * 64	3 * 3	-	-
Relu	31 * 31 * 64	-	-	-
Pooling	15 * 15 * 64	-	2 * 2	-
Conv.4	15 * 15 * 64	3 * 3	-	-
Relu	15 * 15 * 64	-	-	-
Pooling	7 * 7 * 64	-	2 * 2	-
Flattening	1 * 1 * 256	-	-	-
FC Layer	1 * 1 * 256	-	-	-
Relu	1 * 1 * 256	-	-	-
Dropout	1 * 1 * 256	-	-	0,25
FC Layer	1 * 1 * 128	-	-	-
Relu	1 * 1 * 128	-	-	-
Dropout	1 * 1 * 128	-	-	0,25
FC Layer	1 * 1 * 6	-	-	-
Softmax	1 * 1 * 6	-	-	-

Table 1. Architecture created in the proposed CNN model

As can be seen in the table, 256, 128, 64, and 64 filters are defined in the convolution layers, respectively. The L2 regularization is chosen as 0.0002 in these layers, and the ReLu activation function is used to regulate the weights at each stage and thus prevent overfitting. The size of the filters used in the convolution layers is 3x3, and the size of the windows used in the pooling layers is 2x2. In the fully connected layers, a dropout rate of 0.25 is used. In the output layer, six different outputs representing each class are defined, and the softmax activation function, which performs probability calculation for each class, is preferred.

3. EXPERIMENTAL RESULTS

The experimental studies carried out to evaluate the performance and applicability of the CNN deep learning model proposed in this study are presented in this section. For the experimental studies, a computing device boasting an Intel Core i7 central processing unit, coupled with an NVIDIA GTX-1050 4 GB graphics card and running the Windows 10 operating system, is employed. Python 3.8 and the Anaconda distribution system are used to compile and run the code. We also utilized the Keras deep learning library with the Tensorflow backend, which provides a robust framework for deep learning.

In the first stage of the experimental studies, the data set is divided into training, validation, and testing. During the decomposition, 70% of the data are randomly selected for training, 10% for validation, and 20% for testing. In order to prevent overfitting, early stopping is used in the training of the model. The validation accuracy value is chosen as the early stopping criterion, and training is terminated if the value did not increase for ten epochs. Finally, data augmentation is used due to the small number of data in the dataset and the high risk of overfitting. In this context, Phung and Rhee (Phung & Rhee 2018) used the parameters used in their studies to perform data augmentation. The data augmentation process is used only in the training phase of the model and not in the validation and testing phases. In addition, the batch size is 32, the learning rate is 0.0001, and Adam is preferred as the optimization algorithm. In addition, the values in the sky images used as input are normalized in the 0-1 and presented to the model. Table 2 shows the geometric changes and parameter values used during the data augmentation.

Applied Geometric Change	Parameter Value
Rotation	40°
Width Shift	%20
Height Drift	%20
Cutting	%20
Zoom in	%20
Horizontal Rotation	Yes
Vertical Rotation	Yes

Table 2. Geometric variations and parameter values used in the data augmentation process

In order to evaluate the performance of the proposed model, two different error evaluation criteria are used: accuracy and F1 score. Accuracy evaluates the classification algorithm and is calculated using Equation 1 below.

$$A = \frac{\sum_c^C tp_c}{N} \tag{1}$$

In Equation 1 tp_c c is the number of correctly predicted classes, C is the number of classes, and N is the total number of samples. The F1 score measures accuracy that considers both precision and recall. It can be found using Equation 2 below.

$$F1 = \frac{2tp}{2tp + fn + fp} \qquad (2)$$

Experiments are performed with the configurations mentioned above, and the model training is automatically terminated with an early stop at epoch 41. The time variation of training and validation loss values during model training can be seen in Figure 3.

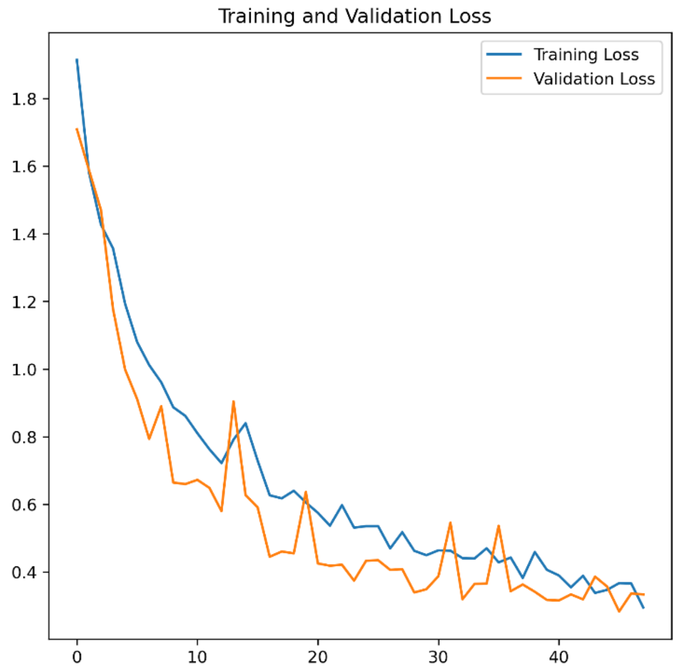

Figure 3. Time variation of training and validation loss values during model training

After the training is completed, the performance and applicability of the model are evaluated with test data. In this context, apart from calculating the accuracy and F1 score, the error (confusion) matrix is also utilized. In the error matrix, the predicted class samples are organized into columns, and the actual class samples are arranged into rows. The diagonal elements of the matrix correspond to accurately predicted values, whereas the non-diagonal elements indicate incorrect predicted values. The error matrix obtained for the proposed CNN deep learning model as a result of the experimental studies is presented in Figure 4.

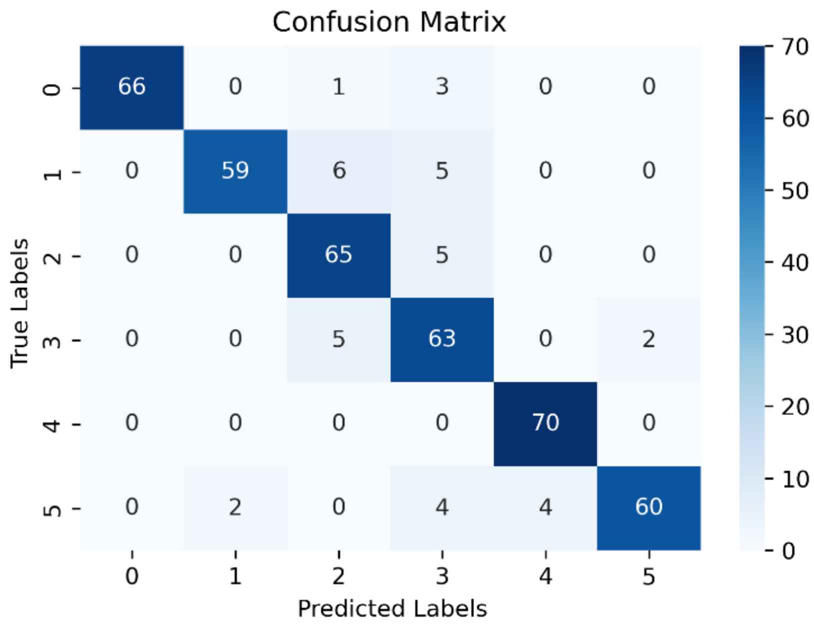

Figure 4. Error matrix obtained for the proposed CNN deep learning model

In the error matrix shown in Figure 4, 0 indicates the clear sky, 1 indicates patterned clouds, 2 indicates thin white clouds, 3 indicates thick white clouds, 4 indicates thick dark clouds, and 5 indicates veil clouds. When the error matrix is examined in detail, it is seen that the proposed CNN deep learning model can classify the clouds correctly to a large extent. However, it is seen that the highest classification error occurs for class 1, with 11 misclassifications. There are also misclassifications in classes 2, 3, and 5, albeit in small amounts. When the prediction results of the model are examined in the areas where misclassifications are realized, it is predicted that these problems are experienced because the class predicted by the model has clouds similar to the actual class. It is also observed that the model could classify the 4th-class clouds entirely correctly. Overall, the results of the experiments show that the CNN deep learning model can successfully predict all cloud classes with high accuracy rates. The precision, recall, accuracy, and F1 score performance metric values calculated using the prediction results of the proposed model are presented in Table 3.

Performance Metric	Metric Value
Precision (Precision - Weighted)	0.924
Recall (Recall - Weighted)	0.917
Accuracy	0.917
F1 Score (F1 Score - Weighted)	0.917

Table 3. Performance metric values calculated for the proposed CNN deep learning model

Considering the calculated error criteria, it is revealed that the proposed CNN deep learning model can be successfully used in the cloud-type classification problem. In addition, it is predicted that the model's performance can be improved by optimizing its parameters. Future studies it is aimed to use the cloud-type classification model created in this study with solar radiation prediction models, thus making solar radiation prediction results more successful.

4. CONCLUSIONS

Clouds have a profound impact on Earth's climate and have been the subject of extensive study in diverse scientific fields, encompassing investigations related to Earth's climate patterns, prediction of atmospheric conditions, atmospheric science, research on harnessing solar energy, and communication via space-based technology. The accurate classification of cloud types based on their optical properties is pivotal for the advancement and application of solar radiation forecasting models. To this end, in this study we have developed a deep-learning Convolutional Neural Network model capable of classifying six distinct cloud types. By utilizing the SWIMCAT-EXT dataset for training and testing, we have demonstrated the model's successful cloud classification performance and its potential integration into solar radiation forecasting processes.

The utilization of the SWIMCAT-EXT dataset for training and testing the CNN model contributes to the development of a more efficient, reliable, and cost-effective solution for cloud classification. Implementing this proposed method in cloud research not only facilitates the acquisition of more precise data without time constraints but also holds promise in refining solar energy prediction models.

It is evident that our research holds paramount importance in predicting the impact of clouds on solar radiation with greater precision, thereby enhancing the reliability of weather forecasting, solar energy research, and related fields. The success of our proposed CNN model underscores the significance of cloud classification research and its potential implications in the development of automatic classification techniques.

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