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Classification of Weather Phenomenon From Images by Using Deep Convolutional Neural Network

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Abstract Weather phenomenon recognition notably affects many aspects of our daily lives, for example, weather forecast, road condition monitoring, transportation, agriculture, forestry management, and the detection of the natural environment. In contrast, few studies aim to classify actual weather phenomenon images, usually relying on visual observations from humans. To the best of our knowledge, the traditional artificial visual distinction between weather phenomena takes a lot of time and is prone to errors. Although some studies improved the recognition accuracy and efficiency of weather phenomenon by using machine learning, they identified fewer types of weather phenomena. In this paper, a novel deep convolutional neural network (CNN) named MeteCNN is proposed for weather phenomena classification. Meanwhile, we establish a data set called the weather phenomenon database (WEAPD) containing 6,877 images with 11 weather phenomena, which has more categories than the previous data set. The classification accuracy of MeteCNN on the WEAPD testing set is around 92%, and the experimental result demonstrates the superiority and effectiveness of the proposed MeteCNN model. Realizing the automatic and high-quality classification of weather phenomena images can provide a reference for future research on weather image classification and weather forecasting.

1. Introduction

The analysis of weather phenomenon plays a crucial role in various applications, for example, environmental monitoring, weather forecasting, and the assessment of environmental quality (Cai et al., 2018). Besides, different weather phenomena have diverse effects on agriculture (Przybylska-Balcerek et al., 2019). Therefore, accurately distinguishing weather phenomena can improve agricultural planning. Furthermore, weather phenomena not only strongly influences vehicle assistant driving systems (by snow, sandstorm, haze, etc.; Yan et al., 2009) but also affects us in our daily lives, such as the wearing, traveling, and solar technologies (Lu et al., 2014; Zhao et al., 2018). Meanwhile, the functionality of many visual systems like outdoor video surveillance is also affected by weather phenomena (Elhoseiny et al., 2015). Additionally, the weather phenomena (haze, snow, sandstorm, and so on) that occurred the day before will also affect weather conditions for the next few days. Local or regional weather conditions such as sandstorms, heavy rain, rime, snow, haze, and agglomerate fog are dangerous weather conditions that could be partly responsible for a large number of traffic accidents on expressways (Lin et al., 2005; Tan et al., 2019). Therefore, we can come to the simple conclusion that the classification of weather phenomena is essential and can help meteorologists to understand climatic conditions as well as improve weather forecasting.

Generally, traditional classification methods of weather phenomena rely on human observation. However, the traditional artificial visual distinction between weather phenomena takes a lot of time and is prone to errors. Hence, there is an urgent need to develop high-precision, efficient, and automated technologies for weather phenomena classification. In recent years, Lu et al. (2014) used a collaborative learning approach for the two-class weather classification (sunny and cloudy). Besides, Pavlic et al. (2013) successfully classified fog and fog-free scenes by using a simple linear classifier. Nowadays, machine learning is developing rapidly, enabling researchers to apply machine learning to various academic fields. For weather phenomena recognition, Song et al. (2014) achieved weather condition

recognition using feature extraction and K-Nearest Neighbor. However, weather phenomenon recognition based on ordinary machine learning can not accurately learn the characteristics of weather phenomena.

Convolutional Neural Network (CNN) is one of the deep learning algorithms. It can provide powerful feature representations for images because of the use of deep structure, local receptive fields, spatial sub-sampling, shared weights, and so on (Liu et al., 2018, 2019; Liu & Li, 2018). Since the AlexNet model (Krizhevsky et al., 2012) achieved success in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC), CNN has been used in many fields, such as face recognition (Parkhi et al., 2015), regression prediction (Chen et al., 2019), and object detection (Girshick, 2015). Recently, more and more studies have applied CNNs to meteorological issues. Guo et al. (2020) used deep CNNs to extract the snow cover from remote sensing imagery. Lu et al. (2019) proposed two cloud recognition architectures based on CNN, and they have improved the accuracy of cloud recognition. On top of this, Dev et al. (2019) integrated daytime and nighttime image segmentation in a single framework by using a lightweight deep learning architecture. They achieved superior results on public databases. In conclusion, it can be seen that CNNs have significant advantages in meteorological image recognition.

Therefore, some studies experimented with the classification performance of CNNs on weather phenomena (Guerra et al., 2018; Shi et al., 2018), such as two-class weather sunny and cloudy (Lu et al., 2017) and three-class weather phenomena (rainy, foggy, and snowy; Wang & Li, 2020). Moreover, Wang et al. (2020) constructed six weather phenomena (including dew, dust, rain, frozen, snow, and haze) and successfully classified them using deep learning. Tan et al. (2020) also successfully realized the classification of six weather phenomena by a three-channel convolutional neural network (3C-CNN). Besides, Zhao et al. (2018) treated weather phenomena recognition as a multi-label classification task. However, these studies just consider a small number of weather categories, and the types of weather phenomena in our daily life are far more numerous and varied. Therefore, it's necessary to consider more kinds of weather phenomena when analyzing and recognizing them in meteorology.

In this paper, we designed a weather phenomenon classification network, named MeteCNN, which is a deep learning algorithm using a data set containing 6,877 images with 11 categories of weather phenomena. Next, we trained the MeteCNN with the prepared training set and then utilized the validation set to validate MeteCNN. Finally, the trained MeteCNN model was evaluated using the testing set. The remainder of this paper is organized as follows. Section 2 introduces the data we used. The proposed classification model and the details of the experimental implementation are described in Section 3. Section 4 presents the results of the experiment and then assesses the MeteCNN model using various evaluation metrics. Finally, Section 5 concludes this paper and discusses the outlook of future work.

2. Data

To the best of our knowledge, a large number of the labeled data set is necessary when proposing any of the classification models in supervised learning. The quantity and quality of the data set directly affect the classification performance of the model (Lu et al., 2019), and the classification accuracy can be significantly improved by creating an extensive database for training and testing (Bankert, 1994; Zhang et al., 2018). Therefore, it is essential to construct an accurate and ample number of labeled weather phenomena images.

In this paper, we initially collected weather phenomena JPG images from the internet and academic exchanges, then manually labeled weather phenomena images using meteorological criteria. Finally, a weather phenomenon database (WEAPD) was established; it was labeled into 11 categories by visual shapes and color characteristics. This database contains a total of 6,877 representative and unique images of weather phenomena (Figure 1). Especially, the WEAPD is composed of hail (592), rainbow (238), snow (621), rain (527), lightning (378), dew (700), sandstorm (692), frost (475), fog/smog (855), rime (1,160), and glaze (639). We divided the WEAPD into the training set, validation set, and testing set in the ratio of 8:1:1, respectively. There is no image overlap among them.

Figure 1. The representative examples of 11 weather phenomena images (these images are from the internet).

3. Method

3.1. Model Architecture

MeteCNN is an optimized CNN focusing on the classification tasks of weather phenomena images. MeteCNN evolves from an improvement of VGG16 (Simonyan & Zisserman, 2014). Compared with commonly used models, VGG16 has a simple structure, is easy to train, occupies a small memory, and can prevent over-fitting for small data sets. Therefore, we choose VGG16 as the framework to build the proposed MeteCNN model. MeteCNN can accurately learn the features of each category of weather phenomenon and has a quality classification effect. As shown in Figure 2, MeteCNN consists of 13 convolutional layers,
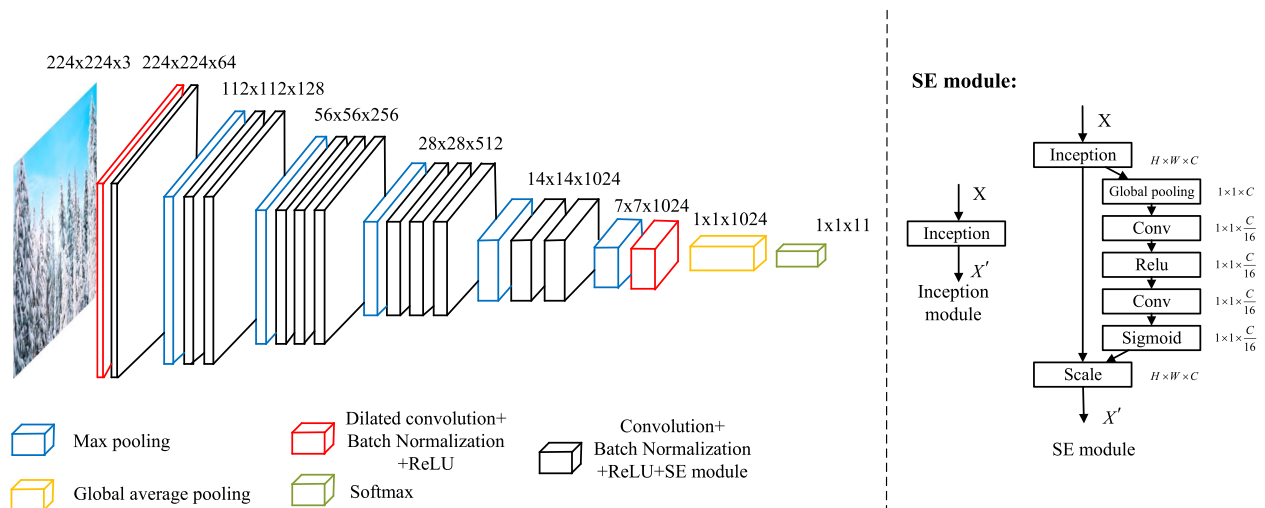

Figure 2. Illustration of the MeteCNN architecture.

six pooling layers (five max-pooling layers and one global average pooling layer), and a softmax classifier. Compared with VGG16, MeteCNN discards the fully connected layers and add a global average pooling layer. The global average pooling layer is before the softmax layer, making the network structure more hierarchical and straightforward.

The squeeze and excitation module (SE module; Hu et al., 2018) is used in our convolutional layers, which is different from VGG16. The SE module, also known as the channel attention, can give different weights to each channel of the feature map and model the correlation between channels. Therefore, the model can identify the most relevant channels, and the trivial information and redundant from other channels are filtered out. The SE module includes squeeze and excitation. As for squeeze, the global average pooling compresses the feature map so that the feature at each channel is an averaged value. After the squeeze values, the attention weight (namely excitation) is generated for each channel through two convolutional layers (with a trainable 1×1 filter bank). Finally, the input feature map at each channel is multiplied with the attention weights to get the final output feature map.

Additionally, the dilated convolution (Yu & Koltun, 2016) is also used in the convolutional layers, while dilated convolution is not used in VGG16. The dilated convolution can enlarge the receptive field, and the convolution output will contain a more extensive range of information. The dilated convolution is designed for the first and last layer of convolution, with dilation of 2, and the other convolutional layers are combined with the SE module. The convolutional layer contains convolution, batch normalization, the Rectified Linear Units (ReLU) function.

The inputs of MeteCNN is a batch of fixed-size weather phenomena images. The convolutional layers act as a feature extractor that transforms input images to abstract weather phenomenon feature representations. Each convolutional layer produces an array of feature maps using a trainable 3×3 filter bank, and the stride is 1. After batch normalization, the ReLU function makes non-linear mapping of the output results from the convolutional layer. The pooling layers subsample their input feature maps with a 2×2 window and stride of 2. The pooling layers can compress the images, and reduce the training parameters, and also can achieve translation invariance. Next, all the local feature outputs by the convolutional layer are combined into global features through the global average pooling layer. Finally, the class probability of feature maps is calculated by the softmax classifier.

3.2. Experiments Settings

The weather phenomena images are initially resized to 256×256. Next, the mean RGB values were subtracted, which were calculated from each weather phenomenon image. After this, for data augmentation, the images were randomly cropped to 224×224, flipped, and rotated, and the method random erasing augmentation was also used. During the training process, the backpropagation and stochastic gradient descent methods (LeCun et al., 1989) are used to optimize parameters of MeteCNN, with a batch size of 16. To prevent over-fitting, we used a weight decay of 5e−4. Besides, we also used the momentum parameters (Sutskever et al., 2013), which have a decay of 0.9. Next, the model is trained to 110 epochs, the initial learning rate is set as 0.001, and the learning rate is reduced to 0.5 times when the loss does not decrease after five epochs. Notably, the validation set was used for adjusting the hyper-parameters of the model (e.g., the settings of learning rate and weight decay) and judging when to adopt early stopping, just as Jing et al. (2019) did. Furthermore, to obtain an effective classification result, the MeteCNN model with the highest validation accuracy was chosen for our test experiments. Our experiments ran on an NVIDIA GeForce GTX1080Ti. The machine learning software package Pytorch (Paszke et al., 2017) was used. The accuracy and cross-loss entropy are estimated after each training and validation epoch. Especially, the accuracy is calculated as follows.

$$\text{Accuary} = \frac{1}{n_{\text{sample}}} \sum_{i=0}^{n_{\text{sample}}} l\left(\hat{y}_i = y_i\right) \tag{1}$$

where the $\hat{y}_i$ stand for the predicted label of the i-th sample and y_i is the corresponding true label. Moreover, the quantitative evaluation metrics were used to evaluate the trained MeteCNN model. Specifically, we adopted the Precision (P), Recall (R), and F_1-measure (F_1) in this paper. Precision represents the ability of

the model not to predict as positive if a sample is negative. Recall represents the capability of the model to find all the positive samples. F_1-measure denotes a weighted harmonic mean of Precision and Recall. The notions of P, R, and F_1 are defined by using true negatives (tn), false negatives (fn), true positives (tp), and false positives (fp) (Zhou, 2016).

$$P = \frac{tp}{tp + fp},\tag{2}$$

$$R = \frac{tp}{tp + fn},\tag{3}$$

$$F_1 = 2 \times \frac{P \times R}{P + R},\tag{4}$$

Furthermore, the macro-average of P, R, and F_1 (ma_P, ma_R, and ma_F_1) can be calculated as follows,

$$ma\_P = \frac{1}{N}\sum_{i=1}^{N} P_i,\tag{5}$$

$$ma\_R = \frac{1}{N}\sum_{i=1}^{N} R_i,\tag{6}$$

$$ma\_F_1 = 2 \times \frac{ma\_P \times ma\_R}{ma\_P + ma\_R},\tag{7}$$

where the evaluation metrics values all range between 0 and 1. The higher the accuracy, Precision, Recall, F_1-measure, and their macro-average values are, and the better the classification performance of the model is.

Finally, accuracy, macro-average of Precision, Recall, and F_1-measure were evaluated against the mainstream models using Resnet18, Resnet34, Vgg16, Vgg19, and the lightweight models, Efficientnet-B7, MobilenetV3, and model proposed by Wang et al. (2020). The experimental settings of these models are the as same as MeteCNN.

4. Analysis of Results

4.1. Feature Maps and Gradient-Weighted Class Activation Mapping

The different semantic meanings can be revealed by feature maps, which are extracted by the hierarchical layers within CNN (Mahendran & Vedaldi, 2014). Meanwhile, the studies presented that the shallow layers are likely to capture texture information, and the deeper layers are prone to show high-level and complex semantic characteristics (Liu et al., 2018; Xiao et al., 2019; Ye et al., 2017). To verify this and understand the training processes, the feature maps of MeteCNN are visualized in Figure 3. Here we only present several channels from the convolutional (Conv) layers 1 to 13. The results show that the shallow layers (e.g., Conv1-1 and Conv3-30) can perfectly rebuild the input weather phenomena images and reflect the profile properties. Meanwhile, the deeper layers (e.g., Conv11-331 and Conv13-600) perform poorly with severe loss of the weather phenomena image profile details, but the deeper layers can learn more complex semantic features. In conclusion, with the deepening of the convolutional layers, the convolutional layer can learn deeper semantic characteristics of weather images, including some non-linear image features. The result is similar to previous research (Liu et al., 2018; Xiao et al., 2019; Ye et al., 2017).

We also provide Gradient-weighted Class Activation Mapping (Grad-CAM; Selvaraju et al., 2016) visualizations in Figure 4 computed at various convolutional layers (take four categories of weather phenomena as example). Here we perform Grad-CAM in different feature maps and analyze how localizations change qualitatively. The results show that the localizations get worse at shallower layers, while after the deepest convolutional layer, the best-looking visualizations are often obtained. In other words, as
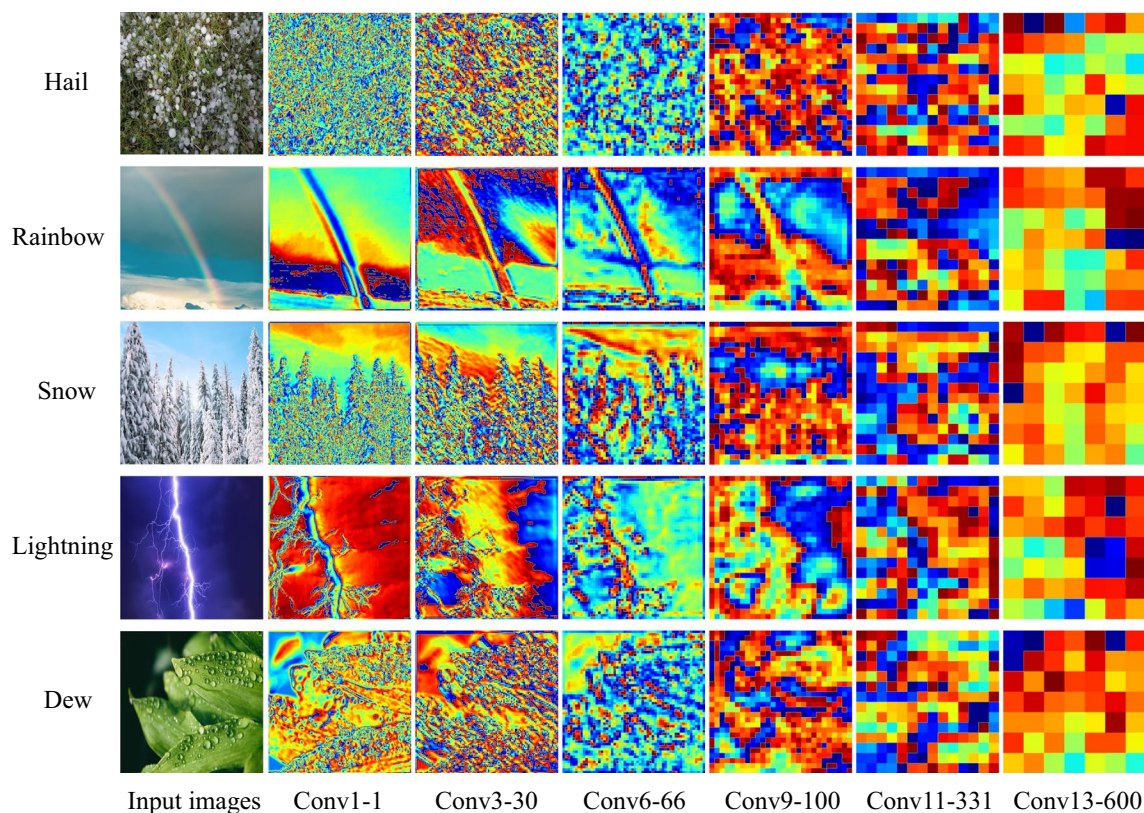
Figure 3. Original weather phenomena images and the feature maps (Conv1-1 (channel number 1 on Conv1), Conv3-30, Conv6-66, Conv9-100, Conv11-331, and Conv13-600) from the different CNN layers. CNN, convolutional neural network.
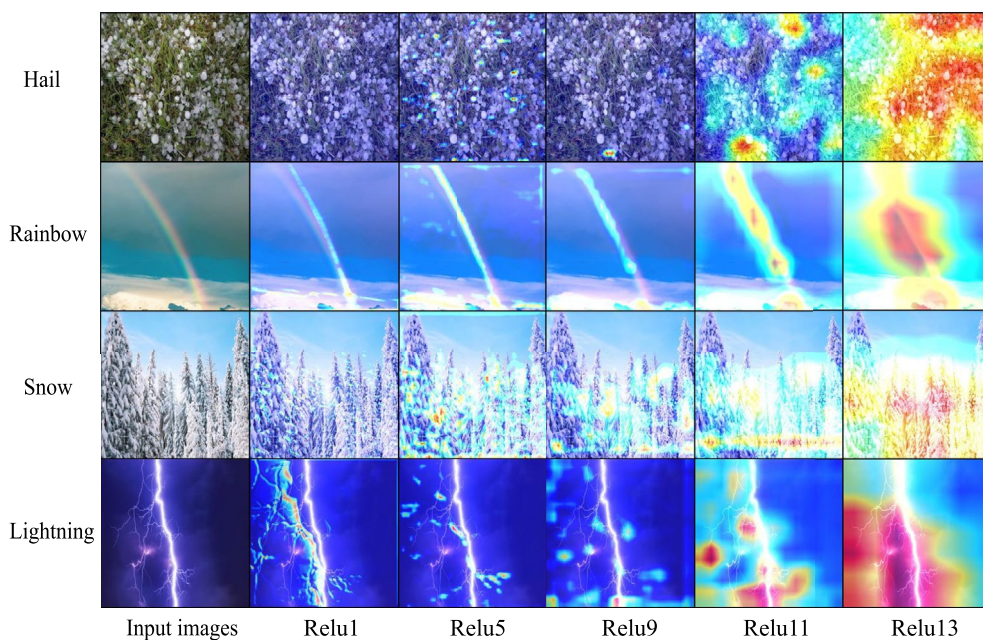

Figure 4. Grad-CAM at different activating layers for the hail, rainbow, snow, and lightning classes. CAM, Class Activation Mapping.

Table 1
Evaluation of the Classification Performance of the MeteCNN Model by Precision, Recall, F_1-Measure

Category	Precision	Recall	F_1-Measure
Hail	0.98	0.98	0.98
Rainbow	1.00	1.00	1.00
Snow	0.85	0.85	0.85
Rain	0.91	0.96	0.93
Lighting	1.00	0.97	0.99
Dew	0.97	0.99	0.98
Samdstorm	0.93	0.99	0.96
Frost	0.93	0.85	0.89
Smog/Fog	0.98	0.94	0.96
Rime	0.88	0.89	0.88
Glaze	0.85	0.84	0.85
Average	0.93	0.93	0.93

the depth of the convolutional layer increases, the model pays more attention to the region of interest. Overall, the Grad-CAM visualizations in MeteCNN can localize relevant image regions well and are class-discriminative.

4.2. Effectiveness of the Proposed MeteCNN Model

The evaluation results of the MeteCNN model by evaluation metrics are presented in Table 1. The MeteCNN model has achieved an effective classification on each type of weather phenomenon, especially for hail, lightning, and dew. In addition, the classification of rainbows is near-perfect, because the Recall value of rainbows is as high as 100%. However, the classification of glaze is inferior. The Precision, Recall, and F_1-measure are just all about 85%. Similarly, the classification of snow is also slightly unsatisfactory, and its classification Precision is 85%. Furthermore, the average Precision, Recall, and F_1-measure of the 11 weather phenomena are all 93%, indicating that MeteCNN can achieve the high-precision classification of weather phenomena.

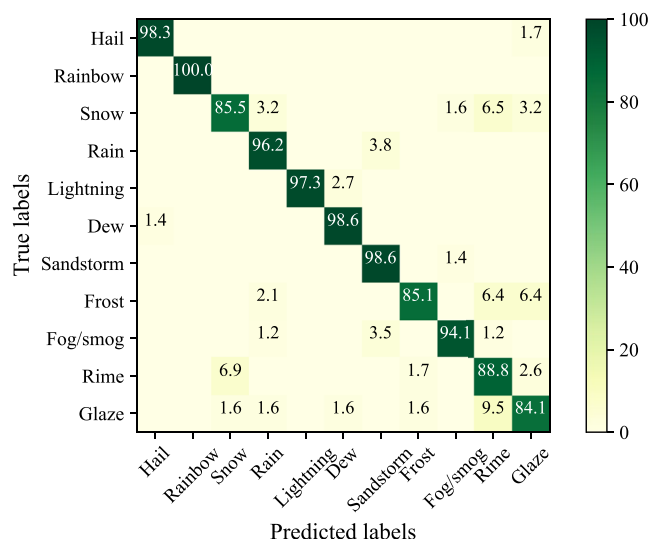Moreover, it is worth noting that the number of image samples is imbalanced. The number of pictures in some categories is small, for example, rainbow (238) and lightning (378), but the proposed model can also accurately classify them (Table 1), with a Recall of 1 and 0.97, respectively. Meanwhile, the category with the first and second-largest number of pictures are rime (1,160) and fog/smog (855), and their Recall is 0.89 and 0.94, respectively. Regardless, a small or large number of images (e.g., rainbow and snow) do not significantly affect the classification results, which demonstrates that the quantity distribution of the data set is reasonable.

To further prove the classification performance of the MeteCNN model on weather phenomena, the confusion matrix was used to illustrate the classification accuracy (Figure 5). The classification accuracy of the MeteCNN model on the weather phenomena is above 84%. However, the MeteCNN model still has some classification errors. For example, for the glaze, the MeteCNN model has the highest probability of confusing it as rime (9.5%), and some glaze images are also incorrectly predicted to be snow (1.6%), rain (1.6%), and dew (1.6%), and frost (1.6%). This may be due to the scenes and shapes of glaze being quite similar to frost or rime, making it difficult for the MeteCNN to distinguish them. Moreover, the probability of the proposed model misclassifying rime as snow is 6.9%, which may be because the colors of the two types of images are very similar. Overall, the proposed model only rarely mis-predicts some kinds of weather phenomena, which may be due to the similarity and complexity of the images.

As we know, the output of MeteCNN is a probability mask, which represents the predicted probability of weather phenomena of different categories. It's necessary to translate the possibility into a specific type of weather phenomenon. In this paper, we employ a Receiver Operating Curve (ROC) technique to investigate the classification ability of the MeteCNN model. The ROC curve of the MeteCNN model for varying probability thresholds in [0,1] on the testing set is presented in Figure 6. When the probability threshold varies from 0 to 1, the True Positive Rate (TPR) and False Positive Rate (FPR) have also changed accordingly (TPR $= tp / (tp + fn)$, FPR $= fp / (tn + fp)$). The areas under the ROC curve (AUC) of each class weather phenomenon are all above 0.96, particularly, the AUC values of hail, rainbow, lighting, sandstorm, and dew are approximately 1.00. It again illustrates that the MeteCNN model can achieve near-perfect recognition on hail, rainbow, lighting, sandstorm, and dew. Besides, the AUC of the macro-average ROC is as high as 0.99, demonstrating the outstanding classification ability of the MeteCNN model.
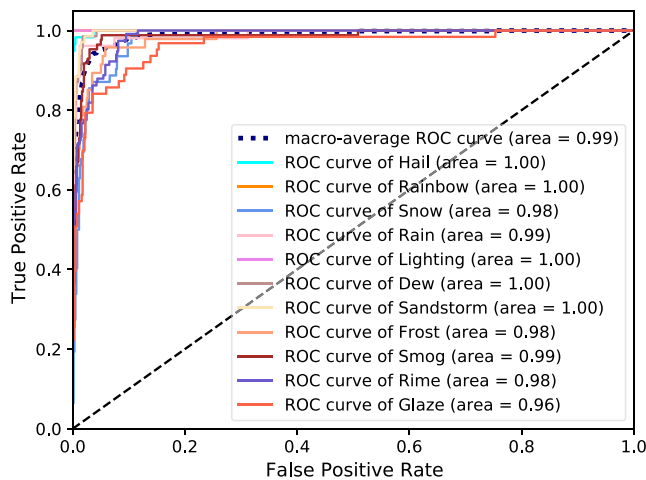

Figure 5. Evaluating the effectiveness of the MeteCNN model by the confusion matrix on the testing set. CNN, convolutional neural network.

Figure 6. The ROC curve of the MeteCNN model on the testing set. CNN, convolutional neural network; ROC, Receiver Operating Curve.

Table 2
Comparison With Other Models by Accuracy and Macro-Average of Precision, Recall, and F_1-Measure

Model name	macro_Precision	macro_Recall	macro_F1	Accuracy
MeteCNN	0.9355	0.9331	0.9340	0.9268
Vgg16	0.8776	0.8750	0.8750	0.8712
Vgg19	0.8531	0.8555	0.8531	0.8521
Resnet18	0.8868	0.8953	0.8901	0.8873
Resnet34	0.8932	0.8955	0.8928	8,858
Efficientnet-B7	0.8819	0.8804	0.8805	0.8741
MobilenetV3-small	0.8507	0.8413	0.8420	0.8404
MobilenetV3-large	0.8770	0.8749	0.8751	0.8712
Wang et al. (2020)	0.8604	0.8522	0.8546	0.8521

Abbreviation: CNN, convolutional neural network.

4.3. Comparison with Other Models

Table 2 shows the performance of the MeteCNN model in comparison to some mainstream models. The overall best classification was the MeteCNN architecture for our weather phenomena data set, with an accuracy of 92.68%. Meanwhile, the macro-average of precision, Recall, and F_1-measure for the proposed model are around 93%. The Resnet18 achieved the second classification on our data set, with an accuracy of 88.73%, which is 4% lower than the MeteCNN model. The results reveal that our model has a competitive classification performance among these mentioned models on our data set.

5. Conclusions

In this paper, we have established a new representative database of weather phenomena images under the meteorological criterion. This database contains 6,877 images with 11 weather phenomena, which has more types than the previous database and can provide a research basis for future weather publicity research. Meanwhile, we proposed a weather phenomenon classification model, MeteCNN, which is a deep CNN model. The MeteCNN model can learn the features of weather phenomena well. Extensive experiments have shown that the proposed MeteCNN model is effective for weather phenomena classification and can avoid the mistakes caused by subjective error, making it superior to traditional methods. However, the MeteCNN model confuses some categories of weather phenomena, which may be due to the similarity and complexity of the images. Overall, the classification accuracy of the MeteCNN model is as high as 92.68%, and the proposed model has a competitive classification performance among some mainstream models (e.g., Vgg16, Resnet34, Efficientnet-B7) on our data set. Therefore, the proposed model can be widely applied to the daily observation of weather phenomenon images and also can provide weather guidance for environmental monitoring, agriculture, and transportation, especially pertaining to weather change and forecasting.

The data set we set up has complex and interference backgrounds. In addition to the object that needs to be identified, each image includes other interference objects. Therefore, interference backgrounds need to be identified and discussed in future research. Besides, we realize that there are many weather phenomena in our daily lives. Thus, more kinds of weather phenomena are needed to be considered in future research. Additionally, the number of pictures of each weather phenomenon can be increased to optimize the classification model and achieve better classification results.

Data Availability Statement

The newly constructed datasets will be available at https://github.com/haixiaxiao/A-database-WEAPD.

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