DOI:

Journal of Computers and Intelligent Systems

Vol. 1, No. 1, 2023, pages 59 - 68

Journal Homepage:

https://journals.iub.edu.pk/index.php/JCIS/

Enhancing Weather Recognition Using Transfer Learning Approach

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ARTICLE INFO

Article History:

Received:	March	04, 2024
Revised:	April	29, 2023
Accepted:	May	02, 2023
Available Online:	May	03, 2023

Keywords:

Multi-Class Classification
Transfer Learning
Fine Tuning

Classification Codes:

Funding:

This research received no specific grant from any funding agency in the public or not-for-profit sector.

ABSTRACT

This research highlights the crucial role of accurate weather classification in industries such as autonomous vehicles and intelligent transportation. Manual classification methods are often time-consuming and prone to errors, while online weather forecasts may not provide real-time accuracy. To address these challenges, the study harnesses the power of Convolutional Neural Networks (CNNs) with the invaluable technique of transfer learning. By using transfer learning, pre-trained models (MobileNetV2 and VGG19) are fine-tuned to classify weather images like Shine, Rain, Sunrise, and Cloudy.

The key significance of transfer learning lies in its ability to leverage knowledge from large datasets, such as ImageNet, to enhance the accuracy and efficiency of weather classification. The results of this study affirm the potential of transfer learning, with MobileNetV2 achieving an impressive accuracy rate of 94.65%, and VGG19 performing strongly at 92.88%. This underscores the critical role of transfer learning in improving weather classification, ultimately providing more reliable weather information for diverse applications and industries. In essence, transfer learning contributes to advancing autonomous systems, outdoor vision solutions, and intelligent transportation, thereby enhancing the quality of life and safety for individuals and communities.

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Citation:

1. Introduction

Weather recognition is the process of using technology, such as computer vision and machine learning, to identify and predict weather patterns. It is important in our daily lives because it allows us to make informed decisions about things like travel plans, clothing choices, and outdoor activities. It also helps in making important decisions for industries such as agriculture, transportation and energy, which are greatly impacted by weather conditions. Accurate weather recognition can also help with disaster preparedness and response, by providing early warning of severe weather events such as hurricanes, tornadoes, and floods.

The information provided about the weather over a certain period of time is crucial for individuals as it impacts their daily routines and actions. People tend to make decisions and plan their activities based on the current weather conditions. This can include things like deciding to go for a bike ride, book a flight, or plan a vacation. Furthermore, the weather is also a factor that is considered when planning business operations, transportation systems, sports events, and sightseeing tours. It's essential to take into account the weather of the location where events are held.

Weather is specific to a particular area and is typically measured through human observations or sensors. However, the local economy may suffer as a result of the high cost of cameras' sensors. With the advancement of technology, it is expected that artificial intelligence (AI) will play a significant role in embedded systems, allowing for more accurate weather analysis while reducing hardware costs. AI is becoming increasingly prevalent in people's lives and has made many tasks easier. Currently, many large companies are utilizing AI in their technologies and continue to invest in its development. Deep learning, a subset of AI, uses architectures with hidden layers to automatically extract features from images, making it a powerful tool in weather forecasting.

There has been a significant amount of research on the subject of weather image classification using deep-learning architectures. In these studies, various methods and techniques have been employed to achieve high classification accuracy. For example, in one study, Zhao et al. used a combination of CNN and RNN models, as well as the LSTM method, to classify five-class weather images. They were able to achieve a classification rate of 92.63%. Another study by Lu et al. focused on classifying aerial images into two categories (sunny and cloudy) and used techniques such as shadow and reflection contrast to extract features from the images. They trained the dataset using a proposed CNN method and achieved a classification success rate of 98.6% with the support vector machines (SVM) using data augmentation.

Elhoseiny, et al. [1] used features found in the fully connected layers of the AlexNet architecture to divide weather images into two classes. By classifying the characteristics that were taken out of the final layer using the SoftMax function, they were able to reach 91.1% accuracy. Guerra, et al. [2] employed three categories of meteorological data in their investigation and utilized the superpixel approach and augmentation approach to enhance pixel seeds uniformly throughout each image. The dataset was classified using the SVM approach after being subjected to numerous CNN model training iterations, and the ResNet-50 model had the highest overall accuracy rate of 80.7%. Overall, these studies have demonstrated that deep learning architectures, particularly CNNs, can be effectively used for weather image classification and have achieved high classification success rates using various techniques such as image augmentation, superpixel method, and feature extraction.

In numerous practical uses, such as systems that assist with self-driving, weather recognition is significant. By limiting vehicle speed and adjusting the intensity of different lights, real-time weather information can increase road safety. Consequently, a few studies concentrated on weather recognition using in-car cameras. A strategy called template matching was suggested in [3] and [4] to recognize raindrops on the windscreen since they often serve as a strong indicator of rainy conditions. Three categories of global features were developed in [3] to discriminate between overcast, sunny, and wet weather. These features included the road information, the histogram of HSV color, and the gradient amplitude histogram. Roser and Moosmann [5] proposed a method of dividing the entire image equally into thirteen parts and extracting different histogram information from each region separately for rain detection. Numerous studies have also examined fog and haze in addition to rainy conditions. Koschmieders Law [6] was used in [7] to calculate the visibility in foggy conditions. In [8] and [9], power spectra were first generated for a given image, and Gabor filters were then employed to extract features for fog recognition. According to edge replies, Bronte, et al. [10] proposal is to use a Sobel filter to identify edges and calculate the existence of fog. In addition, Gallen, et al. [11] used a backscattered veil of lights to specifically find fog at night.

Several weather recognition studies focus on common outdoor photos [12] of estimating weather conditions using illumination calculations on several photos of a specific location. Numerous global features were investigated in [13] to identify weather conditions, power spectral slope, and edge gradient energy, including infection point information, contrast, and saturation. To improve the classification of the weather category, Li, et al. [14] integrated SVM and decision issues with several global characteristics. In contrast to earlier efforts, Lu, et al. [15] suggest a solution to the two-class weather classification problem further using a variety of local factors, including the sky, shadow, and reflection. Zhang et al. made an effort to address the problem of multi-class weather classification in [16] and [17] and used both global and local features to do so. The two-class weather recognition (identical) problem was combined with handcrafted features and CNN features to achieve much better results.

Computers now can observe satellite images determine current weather conditions and make forecasts. This information is easily accessible through the internet, but it is important to note that weather conditions can vary greatly in different locations. In industries such as transportation, real-time weather classification is particularly useful. Self-driving cars, for example, can use weather images to assist in making decisions such as activating wipers in rainy conditions. However, classifying weather images can be challenging due to similarities between different weather conditions, such as foggy and snowy or cloudy and rainy. Image classification is a technology that can help computers recognize weather patterns based on images in real-time. This technology can be used to develop advanced driver Assistance Systems (ADAS) and independent autonomous machines. A study [18] employed AlexNet and CNN with GoogleNet architecture to categorize the weather into four categories: cloudy, wet, snowy, or none of the above. Google Net's accuracy was 92.0% and Alex Net's was 91.1%. The distribution of the training and test data was not described, and there is no information about how the dataset was acquired. For the classification of weather images into the four categories of foggy, rainy, snowy, and sunny, Xia, et al. [19] compared the performance of multiple CNN architectures, including AlexNet, VGG16, and GoogleNet. The best accuracy is achieved by AlexNet, 86.47%. However, there is no information available regarding how long each design takes to compute. CNN and transfer learning were utilized by [20] to classify weather images. Furthermore, it merely made use of binary label classification and VGG16 architecture. There were two labels on the weather image: With Rain (WR) and No Rain (NR). The dataset for this research was gathered from Image2Weather and consisted of dash cam images from the Tokyo Metropolitan Area. This study had an accuracy rate of 85.28%.

Transfer learning is a technique that addresses the fundamental issue of not having enough training data in machine learning [21]. With the premise that the testing and training data are impartial and evenly dispersed, knowledge will be conveyed from one target domain to another. Transfer learning is used in computer vision to expedite the learning process and improve performance. Several image datasets were used to train the pre-trained model, and it will then be retrained using the source dataset. There hasn't been any research, according to prior studies, that tries to identify multiclass weather images utilizing a variety of CNN architectures using transfer learning. This study classifies weather images with 6 different weather kinds, including cloudy, foggy, rainy, shiny, snowy, and sunrise, using numerous CNN architectures, including VGG16, DenseNet201, MobileNetV2, and Xception. To develop a classification model with improved performance more quickly, transfer learning is utilized. ImageNet served as the transfer learning dataset for this investigation. For this work to be comparable to future research, the dataset was gathered from publicly accessible sources such as Kaggle and Camera as Weather Sensor (CWS) [22]. Accuracy, precision, recall, and F1 are the performance criteria used to validate this study. Młodzianowski [23] highlights the importance of weather recognition across various industries, including self-driving cars and agriculture. The proposed solution is an image-based weather detection system that leverages transfer learning to classify weather conditions using a small dataset. The paper presents three weather recognition models based on ResNet50, MobileNetV2, and InceptionV3 architectures and compares their efficiencies. The study [24] evaluates using pre-trained object detection models via transfer learning for tropical storm identification and classification. Compared to bespoke models, it requires less data and offers broader class diversity, achieving accuracies ranging from 69% to 89%, showing promise for efficient and effective storm analysis. The study [25] introduces a novel deep learning model, combining Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), for weather detection and multi-classification based on image processing. Evaluating on a dataset of 10,000 images encompassing five weather conditions, the proposed approach exhibits high accuracy and robustness, outperforming other state-of-the-art models with an overall accuracy of 97.24%. Additionally, a comprehensive parameter analysis underscores the model's efficiency, contributing to the advancement of reliable weather detection systems for diverse applications.

In essence, this study has made several noteworthy contributions, which can be outlined as follows:

Enhanced Multiclass Weather Classification: This study extends the scope of weather classification research by focusing on multiclass classification, encompassing four distinct weather categories, rather than limiting the analysis to binary classification scenarios. This expansion provides a more comprehensive understanding of the complexities of weather classification.

Application of Transfer Learning: A key contribution is the successful application of transfer learning techniques, specifically leveraging pre-trained CNN models (MobileNetV2 and VGG19). This approach harnesses the collective knowledge from extensive datasets and applies it to improve weather image classification, demonstrating the effectiveness of transfer learning in this context.

Exploration of Data Preprocessing: This research also delves into the influence of data preprocessing on the performance of weather classification models. This exploration highlights the importance of data preparation techniques in enhancing the accuracy and reliability of weather classification systems.

The organization of this paper is as follows: Section 1 serves as an introduction and provides an overview of related works. Section 2 provides an in-depth analysis of our proposed approach. Section 3 The outcomes and results of the proposed method are described and analyzed. Section 4 is dedicated to discussing the findings and their implications.

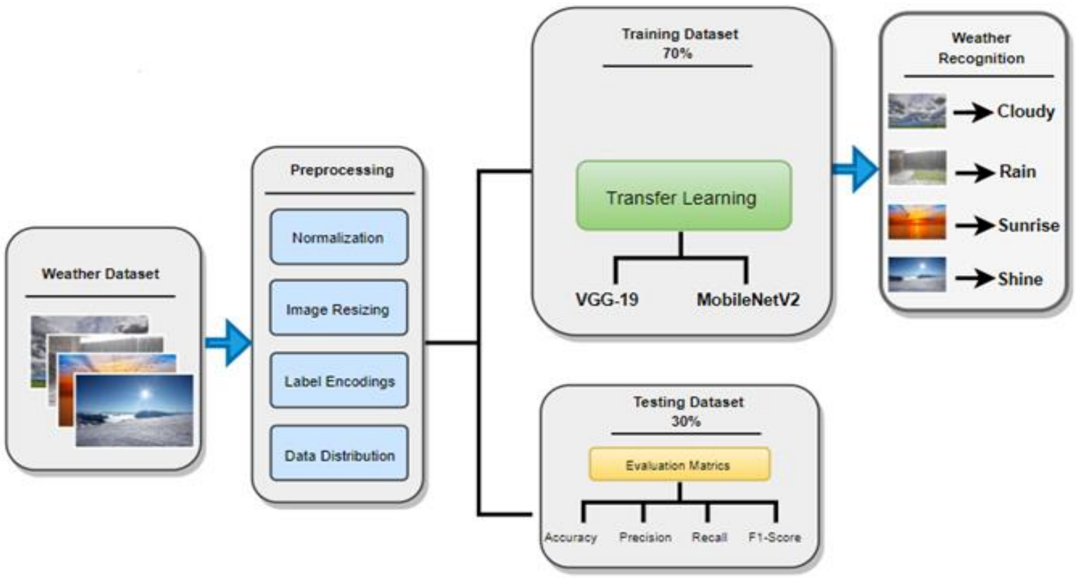

Figure. 1. Abstract Diagram of the Proposed Study.

2. Materials & Methods

An architecture is proposed for a weather classification system that includes the following steps. The first step in the system is to acquire a suitable dataset that can be used for training and testing the models. Before the dataset can be used for training and testing, it needs to be preprocessed. This includes normalizing the data, resizing images to a consistent size, performing label encoding, and distributing the data. The preprocessing module performs these tasks, ensuring that the dataset is ready for the next stage. The preprocessed dataset is split into two parts, a testing set and a training set, using a 70:30 ratio. The train set is used to train two different machine learning models: a custom CNN model and transfer learning models (VGG-19 and MobileNetV2). The test set is used to evaluate the performance of these models by computing various metrics such as precision, recall, accuracy, and F1-score. The final module in the system is the classification module, which predicts the weather class of an image. The models trained in the previous module are used to make predictions, and the results are used to determine the final weather class among four classes (rain, shine, cloudy, sunrise), see Fig. 1 for the abstract diagram.

A. Dataset

This dataset is used for image classification, which is a task in computer vision where a model is trained to recognize and classify different objects or scenes in an image. The considered dataset contains four different classes, which are Sunrise, Shine, Rain, and Cloudy, see Fig. 2. Each class contains a specific number of images. The class "Sunrise" has 357 images, "Shine" has 253 images, "Rain" has 215 images, and "Cloudy" has 300 images. This means that the dataset comprises a total of 1,025 images, with each class being represented by a different number of images. The goal of using this dataset is to train a model to accurately classify an image as one of the four classes based on the image's content.

Figure 2: Weather Classification Dataset: (a) Cloudy, (b) Rainy, (c) Shine, and (d) Sunrise (https://www.kaggle.com/datasets/pratik2901/multiclass-weather-dataset)

B. Data Pre-Processing

For any image classification techniques, image preparation activities are typically an important stage. To get the images ready for feeding into the neural network models in this work, they are carried out over the dataset's original images. Consequently, the images from the gathered dataset are preprocessed as follows:

Normalization: The normalization process on the image dataset by dividing each pixel value by 255. This scaling process brings all the pixel values to a range between 0 and 1. This is a standard preprocessing step in image classification tasks as it ensures that the model is provided with data that has a consistent scale, which can improve the model's performance.

Image Resizing: Resizing images is an important step in image processing as it can help reduce the amount of memory and computational resources needed to work with the images. The goal is to load all the images and check their size, if the size is less than 224x224 pixels then it will print the name and size of the image so that we can decide whether to resize them or not. After checking the size of the images, it was determined that the optimal size for the resized images is 128x128 pixels. This means that all the images will be resized to have a width and height of 128 pixels.

Label Encoding: This process converts categorical labels, such as "cloudy", "rainy", "shiny", and "sunrise" into numerical values comprehensible by machine learning models. We have employed the numeral encoding method, resulting in four labels: "cloudy" is assigned the value of 1, "rainy" is assigned the value of 2, "shiny" is assigned the value of 3, and "sunrise" is assigned the value of 4.

Data Distribution: The final result is two sets of data: a training set, which comprises 70% of the original data, and a test set, which comprises 30% of the original data. These two sets can be used to train and evaluate a machine-learning model.

C. Transfer Learning-Based Models

The transfer learning [26]-[29] method in machine learning entails utilizing a previously trained model for one task as a foundation for building a model for a different task. The idea is to transfer the knowledge learned from the first task to the second task. This is mainly useful when the second task has a limited volume of labelled data. In our research, we used the VGG-19 and MobileNetv2 models, which are pre-trained models that have been trained on a large dataset. By using these pre-trained models as the foundation for our model, we were able to leverage the knowledge learned by these models on a large dataset and fine-tune the models on a multiclass weather class dataset. This allows the model to quickly learn and adapt to the new dataset, as it is already familiar with the general features of the images. This technique helps overcome the challenge of insufficient labelled data and can enhance the model's performance.

3. Results & Discussion

In this study, the same set of hyperparameters was used for the VGG-19 and MobileNetV2 for weather classification. The optimizer chosen was Adam, the loss function used was categorical cross-entropy, the learning rate was 0.0001, the activation function was SoftMax, the number of epochs was 100, and the batch size was 64. This consistent use of hyperparameters across the models allows for a fair comparison of their performance in weather classification tasks, see Table I.

TABLE I: HYPERPARAMETERS OPTIMIZERS

LAYER TYPE	Parameters
Architecture	Transfer learning (TL) models (VGG-19 and MobileNetV2)
TL database	ImageNet
Optimizer	Adam
Dense Layers	16,4
Dropout	0.2
Activation Function	SoftMax
Learning Rate	0.0001
Epochs	100
Batch Size	64
Loss Function	Categorical Cross Entropy

A. Results Comparisons

The results show the performance of two different CNN models on a specific task. The models are MobileNetV2, and VGG-19. Four metrics are used to assess the performance of each model: Precision, Recall, F1-Score, and Accuracy.

MobileNetV2 has an accuracy of 94.65% which is higher than VGG-19. The precision, recall, and F1-score of the MobileNetV2 all are 94.5%. The VGG-19 model has the lowest accuracy of 92.88%. The VGG-19 model has a precision of 92.5%, which is slightly lower than the MobileNet model. The recall of the VGG-19 model is 92.75%, which is also slightly lower than the MobileNet models. The F1-score of the VGG-19 model is 92.5%, see Table II.

TABLE II: RESULT COMPARISON OF VGG-19 AND MOBILENETV2 MODELS

MODEL	Accuracy	Precision	Recall	F1-score
MobileNetV2	94.6	94.5	94.5	94.5
VGG-19	92.8	92.5	92.7	92.5

The classification report for the MobileNetV2 model, as presented in Table III, showcases rounded values for the weighted precision, recall, F1 score, and accuracy, all registering at 0.95.

TABLE III: CLASSIFICATION REPORT OF PROPSOED MOBILENETV2 BASED MODEL

	Precision	Recall	F1	Support

Cloudy	0.94	0.88	0.91	91
Rain	0.98	1.00	0.99	58
Shine	0.90	0.93	0.92	75
Sunrise	0.97	0.98	0.97	113
Accuracy			**0.95**	337
Macro avg	0.95	0.95	0.95	337
Weighted Avg	0.95	0.95	0.95	337

B. Discussion

During the initial epoch, the training loss was 1.6160 and the training accuracy was 0.3676 for the VGG-19 model. The validation loss was 0.8023 and the validation accuracy was 0.7537. This means that the model's ability to accurately predict the correct class la-bels on the validation dataset was 75.37%. By the last epoch, the training loss was 0.0083, and the training accuracy was 1.0000. The validation loss was 0.2157 and the validation accuracy was 0.9525. This suggests that the model's ability to accurately predict the correct class labels on the validation dataset was 95.25%. The model's accuracy can be observed and loss improved as it was trained for more epochs. The model's performance on the validation set also improved from 75.37% to 95.25%, see Fig. 3.

Furthermore, the training loss was 1.5756 and the training accuracy was 0.2270 for MobileNetV2 model. The validation loss was 1.2518 and the validation accuracy was 0.5163. This means that the model's ability to accurately predict the correct class labels on the validation dataset was 51.63%. By the last epoch, the training loss was 0.1094, and the training accuracy was 0.9773. The validation loss was 0.2112 and the validation accuracy was 0.9258. This suggests that the model's ability to accurately predict the correct class labels on the validation dataset was 92.58%, see Fig. 4.

Figure 3: Training and Accuracy Learning Graph of VGG-19 Pretrained Model

Figure 4: Training and Accuracy Learning Graph of MobileNetV2 Pretrained Model

A confusion matrix is a table format utilized to assess the efficacy of a classification algorithm. The table contrasts the predicted classifications with the actual classifications and displays the findings in a matrix form. The predicted classifications are represented by the matrix's rows, while the actual classifications are represented by its columns. The matrix helps to identify the number of false positives, true positives, false negatives, and true negatives which are used to compute several performance metrics such as F1-score, accuracy, precision, and recall. It is called the "confusion matrix" because it helps to understand how the model is confusing between different classes (see Fig. 5 and Fig. 6).

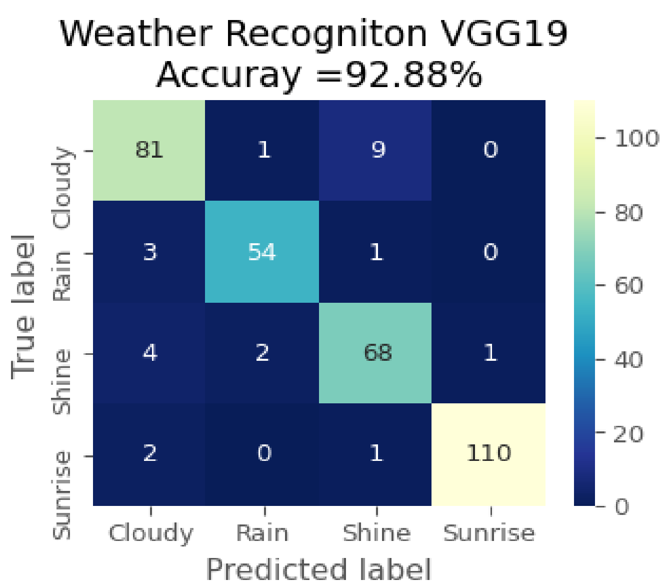

Figure 5: Confusion Matrix of VGG-19 Pretrained Model for Weather Recognition

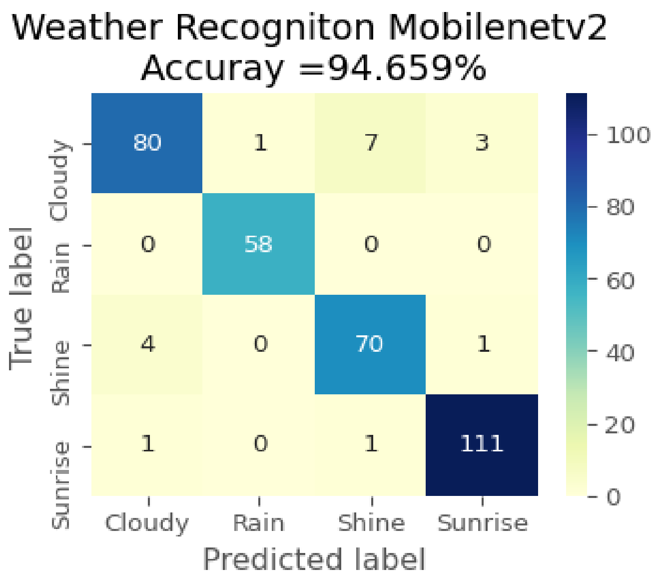

Figure 6: Confusion Matrix of MobileNetV2 Pretrained Model for Weather Recognition

4. Practical Implications

The research's practical implications are far-reaching, spanning various sectors and applications. By harnessing the power of transfer learning and Convolutional Neural Networks (CNNs) for accurate weather classification, industries like autonomous vehicles, intelligent transportation, agriculture, and energy production stand to benefit significantly. Real-time and precise weather classification can enhance the safety and efficiency of autonomous vehicles, optimize traffic flow in intelligent transportation systems, improve crop management in agriculture, and enhance energy generation from renewable sources. Additionally, it can aid emergency response and disaster management, enable targeted marketing and advertising, and contribute to environmental monitoring and research. Ultimately, this technology not only enhances operational efficiency but also improves the quality of life and safety for individuals and communities, making it a valuable advancement for a wide range of industries and applications.

5. Conclusion

In summary, the comparative analysis between MobileNetV2 and VGG-19 models in the context of weather recognition demonstrates that MobileNetV2 outperforms VGG-19. We conducted an accuracy assessment of these models for weather recognition, with VGG-19 achieving an accuracy rate of 92.88% and MobileNetV2 surpassing it with an impressive accuracy of 94.65%. These results unequivocally indicate that MobileNetV2 stands out as the superior model, delivering the highest level of accuracy when compared to VGG-19. As a result, this study strongly suggests that MobileNetV2 may serve as an optimal choice for weather recognition tasks. This recommendation is based not only on its exceptional accuracy but also on its adaptability to resource-constrained devices, making it an excellent candidate for real-world applications requiring efficient and reliable weather classification.

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