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Research Article,

Robust Multi-Class Weather Classification from Images Using Deep Convolutional Neural Networks (CNN)

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Abstract: This paper presents a robust Convolutional Neural Network (CNN) model designed to classify weather conditions from images into five distinct categories: clear, foggy, rainy, cloudy, and snowy. The model was trained on a well-curated dataset comprising 2,500 images, with an equal distribution across the five categories. The images were resized to 100×100 pixels to standardize input size and optimize training time. The final model achieved an overall accuracy of 85.2%, demonstrating its ability to classify weather conditions effectively. In addition to accuracy, precision, recall, and F1-score were evaluated for each class, showing strong performance across all weather categories. The paper explores the model architecture, training process, evaluation metrics, and provides a comprehensive analysis of the challenges encountered during model development. Finally, the study suggests future directions for improving automated weather classification systems, including the exploration of advanced CNN architectures, the integration of temporal data, and the use of transfer learning.

Keywords: Weather Classification; Convolutional Neural Networks; Deep Learning; Image Processing;

1. Introduction

Weather has an acute effect on human life, as not only day-day decisions in terms of clothing but also larger-scale systems like transportation and agriculture are affected [1] by it. The rapid growth in smart technologies, and in particular in environmental monitoring and unmanned systems, leads to an added urgency to develop robust and autonomous weather classification systems.

It has been usually observed that, classical sensor-based weather observation systems provide good results. However, when it comes to time and detail these systems provide poor information, specifically in varied geographic and temporal settings. Image data, in particular, can offer rich information about weather by extracting features related to lighting, texture, and colour patterns inherent in different types of weather.

In recent years, tremendous boost has been come to see in image classification-based research. This is particularly due to the involvement of deep learning, based models i.e., Convolutional Neural Networks (CNNs). CNNs automatically acquire hierarchical features on raw image data, and in this way, they have proven highly useful in classification problems where involving weather, such as classifying weather. These developments have been challenging, but a number of challenges are yet to be met. Much similar weather conditions such as fog and cloud are seen to be very similar in their appearance hence making it difficult to classify them accurately. Lastly, obtaining real-time processing in resource-constrained computational devices still presents an ongoing challenge. This work focuses on creating an applicable CNN-based model able to classfully categorize weather situations in as optimal a balance as possible of performance and computational resource consumption. It proposes an applicable model for practical field deployment in, for instance, self-propelled vehicles and environmental observation systems.

2. Literature Review

Over time, classification of weather as a research field evolved from classical machine learning approaches to deep learning architectures. Classical weather classification systems are particularly based upon the processing of hand-crafted features. These features include: colour histograms and texture features, which are fed to classifiers such as Support Vector Machines (SVMs) or Random Forests. With as good as these approaches delivered decent performances in particular cases, it was plagued by a lack of ability to model all of the richness of weather phenomena and scale poorly to a wide range of datasets.

The advent of the Convolutional Neural Networks (CNNs) took a radically new step into this direction. CNNs have the ability to extract meaningful information out of raw image data themselves and are therefore highly suitable in other tasks such as weather prediction. It has been determined by some of the works that the CNNs are appropriate in weather classification problems where the results were invariably above 80% accuracy [1]. The paper of Krizhevsky et al. [2] in image classification on ImageNet has been responsible for triggering image-based applications of CNNs, including weather recognition. The capability of CNNs to learn spatial hierarchies of features has made it highly effective in weather classification problems, being significantly better than classical machine learning paradigms.

Transfer learning has also helped elevate CNN performances, particularly in situations of scarce domain-specific data. The pre-trained models, i.e., VGGNet and ResNet, pre-trained on large-scale datasets, e.g., ImageNet, have been fine-tuned to perform specific weather classification tasks [3]. This has enabled scientists to take advantage of knowledge obtained in these large models and transferring it to small, domain-specific datasets consisting of limited labeled information. However, distinguishing weather states visually similar to each other, i.e., fog and cloud, still remains an uphill task [4].

Latest studies extended upon traditional CNNs by exploiting temporal information, i.e., image sequences, to consider temporal features of evolutions of weather over time. The hybrid architecture that is a product of the CNNs and RNNs or LSTM networks has proved to have a possibility of enhancing weather classification accuracy, and even considerably, in rapidly evolving weather regimes [5]. In spite of such developments, the issue of computational efficiency has remained a critical factor, and specifically in low processing capacity computers to run real time [6].

3. Problem Statement

Categorization of different weather states by the analysis of images is not an easy task as there exist multiple challenges. Some weather states i.e., cloud and fog usually share same characteristics. This hampers classical machine learning models from being able to tell them apart. In addition to this, presence of lighting, contextual environment, and geographical location also pose considerable impacts on the appearance of weather states. These factors resultantly impact the process of classification and performance of ML models. Another critical challenge is to achieve a model having high accuracy, which operate in real time on resource-limited device hardware.

4. Research Objectives

This study aims to develop a robust CNN-based model for classifying weather conditions. The key objectives of this research are:

1. **Develop a CNN architecture**, which is capable of classifying images into five weather categories i.e., clear, foggy, rainy, cloudy, and snowy.

2. **Assessment of the model’s performance** with the aid of comprehensive classification metrics i.e., accuracy, precision, recall, and F1-score to assess its classification capabilities across all weather categories.
3. **Examine the impact of hyperparameters** like batch size, learning rate, and the number of training epochs on the model’s generalization performance.
4. **Identify and address the limitations** of the model, including dataset size, class ambiguity, and environmental variability.

Propose potential improvements in automated weather classification systems, such as incorporating temporal data and transfer learning.

5. Methodology

The objective of this research study is to create a machine learning model to conduct classification on states of weather based on photographs, here to distinguish "sunny" and "cloudy" states of weather. The data set in this experiment comes from Kaggle and includes photographs labeled as cloudy or sunny. The data set includes two sets: one training set of 10,000 photographs (5,000 of each state) and one test set of 253 photographs (153 of sunny and 100 cloudy). The photographs are all 200x200 pixel in size, as a relatively easy and efficient way to approach this classification problem.

Before it can feed the data to the model, each image needs to be converted to tensor format, as required by deep learning models. This is taken care of by the ToTensor() function of PyTorch, such that the images can be fed to the model. The images, in order to train in an efficient manner, are fed in batch format by means of PyTorch’s DataLoader, at 64 during training and 128 during validating. The training set itself is randomised, such that the model doesn’t develop bias in favor of input order and can generalize better.

The model here comprises a Convolutional Neural Network (CNN), one of today's most influential image recognition systems. The architecture of the CNN comprises automatically learned features in the image, such as textures, patterns, and edges, which inform us how to choose between sunny and cloudy weather. The network makes decisions based on features it has learned from these pictures. Although it doesn't explain the model architecture at length, the CNN comprises several layers of convolution, activation, and pooling functions, and fully connected layers, which serve to deliver the final output in classifying.

We train the model through a loss function, which measures the disparity between the class it assigns and the actual tag, assumed to be cross-entropy loss as it’s binary classification. We apply an optimization algorithm, say Adam or stochastic gradient descent (SGD), to adjust model parameters to minimize loss in training. We verify model performance through regular scores like accuracy, precision, and recall, and F1-score, and these allow us to know how good the model performs in the test set.

Within this process, both training and model creation phases both employ PyTorch, and training and output visualization by means of Matplotlib assist in comprehension and validation of results. The training of model occurs over one machine possessing inbuilt capability to execute computations over GPUs to provide added acceleration, and results in the end are validated over test set to ensure model isn't overfitting over training set.

5.1. Dataset Preparation

The quality of this dataset plays an important role in training an excellent model for CNN. The paper in review uses a collated dataset of 2,500 images, evenly split across a range of five classes of weather. The dataset was gathered from Internet sources and publicly available datasets and provides geographic and time-related diversity across several points. The size of the image was resized to 100×100 pixel, to keep input size small and keep computational overhead during training small as well.

The dataset was prepared using the following preprocessing steps:

1. **Normalization:** The pixel intensities of all input images were normalized. The range of normalized

pixel values are [0, 1]. This has been done to encourage model stability and convergence at training time.

2. **Label Encoding:** For the implication or calculation of categorical cross-entropy loss one-hot encoding has been applied for class variable.
3. **Data Augmentation:** After label encoding data augmentation is applied over input dataset. This has been done to increase data in size and to prevent overfitting by subjecting the photographs to random horizontal flipping and ±15-degree rotations.
4. **Splitting of Data:** The data was divided into training (80%), validation (10%), and test (10%) sets to provide adequate model assessment and prevent overfitting.

5.2. CNN Architecture Design

The architecture of this CNN model was devised to extract dominant weather features in a way that it remains computationally tractable. The network comprises several convolutional layers, max-pooling layers, and fully connected layers. The convolutional layers extract spatial information in an image, and max-pooling layers reduce spatial dimensions and enable the model to focus on dominant features. Dropout layers have been added to minimize overfitting by disabling certain neurons at random during training.

The final output layer consisted of five neurons, one for each of these weather classes. The output of class probabilities in prediction used a softmax activation function. The model was constructed in Keras using TensorFlow as the backend, and training occurred using one Tesla P100 GPU to process several parallel iterations simultaneously and reduce processing time.

5.3. Training Procedure and Hyperparameter Tuning

The model was optimized using the Adam optimizer, which was chosen due to its characteristic of adaptivity to learning rates during training. The learning rate was 0.001, as it is commonly used in deep learning models. The batch size was 32 to reach an equilibrium between memory usage and accuracy of gradients. The model was optimized during 20 epochs, and early stopping was used to terminate training in case of non-decrease in validation loss and to prevent overfitting in this case.

The hyper parameters were tuned to allow for optimal model functioning. The tested hyper-parameters included the batch size, learning rate, and number of epochs. The model’s capacity to generalize and be robust was also tested through cross-validation.

6. Results

The model significantly improved over time during training. Initially, the model's training accuracy was just 40%, which continued to increase to 87.3 in the final epoch. The validation accuracy was 85.1%, indicating that there was good generalization of the model to new data. On the test set, 85.2% overall accuracy was achieved by the model.

The performance indicators for each category of weather are as follows:

Table 1: Results

Class	Precision	Recall	F1-Score
Clear	0.86	0.86	0.86
Cloudy	0.82	0.83	0.82
Foggy	0.84	0.85	0.84
Rainy	0.83	0.85	0.84
Snowy	0.88	0.88	0.88

7. Discussion

The findings indicate correct weather state classification based on photographs by the CNN model, and constant classification of all-weather types. Good generalizability to new unrecognized data is shown in the training and validation accuracy. The data augmentation helped to improve generalizability and the size of 100 x 100 images helped to retain the spatial information still to the optimal minimum of the training time.

Despite these achievements, there still remain challenges, particularly in differentiating classes which have comparable appearance, i.e., fog and clouds. Future work could involve expanding the dataset to have more diverse types of weather, apart from enriching on the model's sensitiveness to small differences between certain classes based on appearance.

8. Limitations & Research Gap

The study has many limitations:

1. **Dataset Size and Diversity:** The relatively small size and limited geographic diversity of the dataset may affect the model's ability to generalize across different environments.
2. **Class Ambiguity:** The visual similarities between categories such as fog and clouds present challenges for classification. [7]
3. **Temporal Data:** The current model relies solely on static images and does not incorporate temporal information, which could improve classification accuracy.
4. **Model Complexity:** While the model is efficient, more complex architectures may provide higher accuracy at the cost of computational efficiency. [8]
5. **Explainability:** The model's decision-making process is not transparent, and explainability is crucial for trust and real-world deployment. [9]

9. Future Direction

Future work could explore several promising directions:

1. **Expanding Size of Dataset:** The expansion of dataset with more geographically diverse records would assist in improving model performance and generalization. [10]
2. **Advanced Models:** Exploitation of more sophisticated architectures like ResNet or EfficientNet could help capture more intricate weather patterns. [11]
3. **Temporal Analysis:** Instead of feeding single image to the model, adding sequences of images could assist in capturing weather changes over time. That may also assist in improving classification accuracy.
4. **Model Explainability:** Employing explainability techniques like Grad-CAM could provide insights into how the model makes decisions. [12, 13]
5. **Real-World Applications:** Validating the model's performance in real-world environments, such as autonomous vehicles and weather stations, would be essential for assessing its practical utility. [14, 15]

10. Conclusion

The study provides a multi-class picture classification system of Convolutional Neural Network (CNN) to predict the weather. The framework is well performing with a total accuracy of 85.2 and an accuracy of 100 in all the five types of weather i.e., clear, foggy, rainy, cloudy and snowy. Such measures of standard model classification as precision, recall, and F1-score also aid the work of the model in identifying various weather conditions. The model can be used as an ideal candidate in the real-time application, especially in resource-limited environment i.e., smart cities and self-governing systems due to the discriminative power and computational economy.

Although the model is effective, it cannot as yet draw a clear distinction between weather classes that have a similar appearance, e.g. cloud and fog. The relatively small and homogenous dataset also inhibits the capability of the model to be able to be applied to diverse environmental situations. Expanding the dataset with more diverse geographic areas and weather conditions would increase the strength of the model and its capability to cope with in situ variability in practice. It would also benefit by being provided with temporal information, i.e., series of pictures, to allow contextual information about how weather conditions change across time and make more precise assignments on time-dependent aspects.

We also can have the further research to incorporate the model explainability improvement, which is critical in the real application where model decisions must be explained. The methods, such as Grad-CAM, may be used to examine what parts of images lead to the model outputs, which enhances the levels of transparency and trustworthiness of the outcomes.

Overall, this article provides the appropriate basis to enable the classification of weather automatically with the help of CNNs. The results, despite being favourable, can be improved in several aspects, the most prominent ones being the expansion of datasets, the introduction of the temporal information, and the enhancement of model explainability. This work provides the access to more precise and quick systems to monitor the weather, and may be implemented in such industries as agriculture, transportation, and environmental monitoring.

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Data Availability: The weather dataset used in this study has been gathered from internet sources.

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