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# Predicting Weather Conditions from Images

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## ABSTRACT

*Convolutional neural networks (CNNs) are widely acknowledged in the fields of image and video recognition, face recognition, image analysis, image classification and activity detection. CNNs take images as their input; assign adaptive weights and biases to numerous features of the image; and then assign the various categories to them.*

*The intent of this paper is to establish a model to classify outdoor images to different weather classes. Literature survey about the field related to weather prediction has shown that the best results are obtained while using the CNN models. This paper proposes a method of implementation of convolutional neural networks to classify separate weather conditions into four classes, namely cloudy, rainy, shine and sunrise. In this paper, four CNN models with different number of model layers are implemented and their results are examined.*

**KEYWORDS:** *Convolutional neural networks, image classification, sequential model, model layers*

## I. INTRODUCTION

Currently, in the field of weather detection, many expensive and complex sensors are used; which are not even obtainable by all. As opposed to using these inaccessible hardware devices; surveillance cameras or even smartphones' cameras can be used to detect the weather conditions. The model we are proposing will take input in the form of an image and then classify that particular image to one of the four classes: cloudy (figure 1), rainy (figure 2), shine (figure 3) and sunshine (figure 4). Many factors of the image like color brightness, haze and contrast are considered for the analysis of these conditions.

Weather detection can be utilized in many research fields and can provide inputs to many higher level processes. It can be used in driver-less vehicles for regulating the speed of the vehicle, setting the vehicle's speed according to the speed associated with weather condition at that particular time[13]. This method can also be applied to the speed limit sign boards; making those sign boards more robust according to the real-time weather surroundings[9].

Figure 1: Cloudy

Figure 2: Rainy

Figure 3: Shine

Figure 4: Sunrise

This classification can even be utilized as a separate filter in various applications or even in the photo gallery of every individual. The same classification can also be exercised as a search tool in smartphones to find images with a certain weather surroundings.

The proposed model can also be used for local hazard warning[13]. The Local Hazard Warning tries to countervail hazardous situations by using information from vehicles that are present on the road at the moment and then provide a warning to others who are heading towards those locations. A vehicle that is in a situation with dense fog can detect and send the related information to the authority in charge; hence warning others to use alternate resources.

## II. RELATED WORK

H. Kurihata, T. Takahashi, I. Ide, Y. Mekada and H. Murase (Graduate School of lnformation Science, University of Nagoya, Japan) Y. Tamatsu and T. Miyahara (Denso Corporation, Japan) proposed Rainy Weather Recognition from In-Vehicle Camera Images for Driver Assistance[2]; they developed a weather recognition method from in-vehicle camera images that uses a subspace approach to predict rainy weather. They judged rainy weather by detecting raindrops on the windshield. They used a subspace method that extracted features using principal component analysis (PCA) from images that have common features.

UthaiPhommasak , Shinya Watanabe and Hiroyuki Shioya (Department of Information and Electronic Engineering, Muroran Institute of Technology, Japan) Jun Mao (College of Computer Science and Technology, Henan Polytechnic University, China) presented Detecting Foggy Images and Estimating the Haze Degree Factor[5]; they introduced a numerical foggy image detecting method by using the atmospheric scattering model analysis and statistics of various outdoor images. Their model could estimate the haze-factor by using an adjustable empirical function without any manual input constraints. Because its complexity is linear, it can be applied as an initial classification step of de-hazing processing and does not exhaust processing resources.

Wei-Ta Chu, Xiang-You Zheng and Ding-Shiuan Ding (National Chung Cheng University, Minxiong, Chiayi, Taiwan) brought forward Image2Weather: A Large-Scale Image Dataset for Weather Property Estimation[6]; they have presented a large-scale image dataset where they captured images from all around the Europe. There images present rich weather information obtained from a weather forecast website. This information rich dataset thus brings many research potentials in the computer vision society. They used KNN classifier and random forest classifier and found that random forest classifier outperforms the KNN classifier.

Cewu Lu and Chi-Keung Tang (The Hong Kong University of Science and Technology) Di Lin and JiayaJia (The Chinese University of Hong Kong) suggested Two-Class Weather Classification[8]; they have proposed a learning-based approach for classifying two types of weather: sunny and rainy. This simple two class weather labeling problem is not useful to a large extent as there is a great

variety of outdoor images available. The key to their computational framework is a collaborative learning strategy with the SVM model, where only voters closer to the testing image information/structure are given more weight in classification.

## III. METHODOLGY AND APPROACH

As stated in the abstract, our aim is to develop a model that can predict weather conditions from the image. At the beginning; we have researched and analyzed many related works and papers[2][5][6][8]. We collected useful information regarding image recognition and image classification. Also, we found that convolutional neural network outperforms all other machine learning algorithms when it comes to image classification. Accordingly we have used convolutional neural networks for our model.

*Dataset and organizing the data.*The dataset we used incorporate a total of 1125 images in jpeg format[6][8][14]. These 1125 images are divided into four classes: cloudy, rainy, shine and sunrise (As shown in table 1)

| Class | Train | Validation set | Test set | Total |
|---|---|---|---|---|
| Cloudy | 220 | 50 | 30 | 300 |
| Rainy | 170 | 30 | 15 | 215 |
| Shine | 180 | 40 | 33 | 253 |
| Sunrise | 260 | 50 | 47 | 357 |
| Total | 830 | 170 | 125 | 1125 |

Table 1: Distribution of dataset used

*Resizing images:* Before performing any function on the images; all pictures used were first resized to a uniform size of 224x224 pixels and were arranged in different folders for each class (cloudy, rainy, shine and sunrise) and for every set (train, validation and test).

*Convolutional neural networks.*CNNs are widely popular among classification algorithms. They are one of the advanced algorithms of machine learning field. Currently, there are many libraries that can implement CNNs. Keras library which uses Tensorflow back end is one of the most popular library of the field. We have used the sequential model of the Keras for our project. We have done lots of experiment on them to get better and an efficient model.

A CNN is made up of multiple layers of neurons, each of which performs operation, which is nonlinear in nature, on the outputs received from the preceding layer. The layers mainly include convolutional layers, pooling layers, a flatten layer and some dense layers.

## IV. EXPERIMENTAL RESULTS

We tried four CNN models to develop a solution to this image classification problem. General accuracies of all models used lie between 65-85%. Following tables show the Information regarding the models developed along with their respective results:

Model 1 with accuracy 81.4%

| **Layers** | **Parameters** |
|---|---|
| Conv2D | filters=32, kernel_size=(3, 3), activation='relu', padding = 'same', input_shape=(224,224,3) |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Conv2D | filters=64,kernel_size=(3,3), activation='relu',padding='same' |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Flatten | none |
| Dense | units=4,activation='softmax' |

Table 2: CNN model 1 architecture

Model 2 with accuracy 75.7%

| **Layers** | **Parameters** |
|---|---|
| Conv2D | filters=32, kernel_size=(1, 1), activation='relu', padding = 'same', input_shape=(224,224,3) |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Conv2D | filters=32,kernel_size=(5, 5), activation='relu',padding='same' |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Flatten | none |
| Dense | units=100,activation='relu' |

| | |
|---|---|
| Dropout | Value=0.5 |
| Dense | units=4,activation='softmax' |

Table 3: CNN model 2 architecture

Model 3 with accuracy 67.2%

| **Layers** | **Parameters** |
|---|---|
| Conv2D | filters=32, kernel_size=(1, 1), activation='relu', padding = 'same', input_shape=(224,224,3) |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Conv2D | filters=32,kernel_size=(2,2), activation='relu',padding='same' |
| MaxPool2D | pool_size=(2,2),strides=2 |
| Conv2D | filters=32,kernel_size=(5,5), activation='relu',padding='same' |
| Flatten | none |
| Dense | units=100,activation='relu' |
| Dropout | value=0.5 |
| Dense | units=10,activation='relu' |
| Dropout | value=0.3 |
| Dense | units=4,activation='softmax' |

Table 4: CNN model 3 architecture

Model 4 with accuracy 66.5%

| **Layers** | **Parameters** |
|---|---|
| Conv2D | filters=32, kernel_size=(1, 1), activation='relu', padding = 'same', input_shape=(224,224,3) |
| MaxPool2D | pool_size=(2,2) |
| Dropout | value=0.5 |
| Conv2D | filters=32,kernel_size=(3,3), activation='relu',padding='same' |
| MaxPool2D | pool_size=(2,2) |
| Conv2D | filters=32,kernel_size=(4,5), activation='relu',padding='same' |
| Conv2D | filters=32,kernel_size=(5,5), activation='relu',padding='same' |
| Flatten | none |
| Dense | units=100,activation='relu' |
| Dropout | value=0.5 |
| Dense | units=4,activation='softmax' |

Table 5: CNN model 4 architecture

## V. Some Common Mistakes

The word "data" is plural, not singular. The subscript for the permeability of vacuum $\mu_0$ is zero, not a lowercase letter "o." The term for residual magnetization is "remanence"; the adjective is "remanent"; do not write "remnance" or "remnant." Use the word "micrometer" instead of "micron." A graph within a graph is an "inset," not an "insert." The word "alternatively" is preferred to the word "alternately" (unless you really mean something that alternates). Use the word "whereas" instead of "while" (unless you are referring to simultaneous events). Do not use the word "essentially" to mean "approximately" or "effectively." Do not use the word "issue" as a euphemism for "problem." When compositions are not specified, separate chemical symbols by en-dashes; for example, "NiMn" indicates the intermetallic compound $Ni_{0.5}Mn_{0.5}$ whereas "Ni–Mn" indicates an alloy of some composition $Ni_xMn_{1-x}$.

Be aware of the different meanings of the homophones "affect" (usually a verb) and "effect" (usually a noun), "complement" and "compliment," "discreet" and "discrete," "principal" (e.g., "principal investigator") and "principle" (e.g., "principle of measurement"). Do not confuse "imply" and "infer."

Prefixes such as "non," "sub," "micro," "multi," and ""ultra" are not independent words; they should be joined to the words they modify, usually without a hyphen. There is no period after the "et" in the Latin abbreviation "*et al.*" (it is also italicized). The abbreviation "i.e.," means "that is," and the abbreviation "e.g.," means "for example" (these abbreviations are not italicized).

An excellent style manual and source of information for science writers is [9].

## VI. CONCLUSION

In this paper, we used convolutional neural networks for classifying images according to the weather conditions. We were able to get accuracy of

up to 81.4%. The hardest part was to decide on the CNN architectures, because of many variations and trying each architecture takes too long to train. Also, the dataset we used was too small to rely upon to solve real time problems. If we had strong GPUs, we could try a much larger dataset and find better solutions.

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