Cloud Image Classification on a Smartphone

Trail Sense / Kyle Corry

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Abstract

This paper describes the need for and a solution to cloud image classification that can run locally on a smartphone. Such a system would allow offline weather prediction based on clouds and how they change over time. The system described in this paper is used in the Trail Sense app on Android.

Keywords

clouds, classification, machine learning, smartphone, weather

1 Problem Statement

Clouds have been used for centuries to predict weather[1], so knowing what type of cloud is present can enable better informed weather prediction by both on-device algorithms and users.

While it is possible for users to identify and enter which clouds they see, it would require the user to have knowledge of cloud type, which is not guaranteed. Descriptions or dichotomous keys[2] can be used to help alleviate the problem, but they are open to user interpretation and can be cumbersome. Therefore, a system which relies upon users to identify clouds may lead to frustration and poor reliability.

An algorithm for identifying clouds using an image could address some of these problems. First, this system would be user independent, therefore eliminating the need for them to have knowledge about clouds. The accuracy of this system could be validated using a collection of labeled cloud images. Such a system would still be impacted by the device's camera hardware and the correctness/number of labeled image data used to train and validate the algorithm.

In order to run on smartphone hardware and remain performant, such an algorithm may also need to find a balance between accuracy, memory, time/complexity, and storage space.

2 Background

There are 10 genera of clouds which are commonly recognized, with each having a distinct set of characteristics to differentiate them[3]. The characteristics show themselves visually through cloud cover, texture, and color. In general, low-level clouds have more visible detail than high-level clouds, and stratus clouds have more consistent color and take up the whole sky.

Using an image classification algorithm to identify cloud images isn't new, and there are several existing solutions. One such solution is the Cloud Appreciation Society's CloudSpotter AI, available as a mobile application, allows the user to take a photo of a cloud and it can identify the genus or even species of the cloud. The classification appears to happen on a remote server, since enabling airplane mode will disable classification[4].

Another study, out of Kiel University, had success in detecting the genus of a cloud based on spectral and textural features of the image. In the study, features were extracted from an image taken by a stationary sky camera and used as data points in a KNN classifier. Their algorithm achieved a 97% accuracy using their validation set (and a 75% accuracy on random images)[5].

The team at Kiel University used a metric called NRBR, or Normalized Red-Blue Ratio, to differentiate between clouds and sky. This metric can be calculated as (red - blue) / (red + blue). This works because the ratio of red and blue is different between clear sky and clouds, where light gets scattered among the water droplets[5].

Kiel University's study also made use of a GLCM, or Gray Level Co-occurrence Matrix. A GLCM is a matrix computed using a single channel of an image which represents the difference in brightness between pixels. Techniques can be used to make the GLCM direction invariant, meaning it checks the difference in brightness in all directions[6]. In addition, reducing the number of gray levels in the image can make the GLCM more robust to random sensor noise[7], using 16 - 32 levels is recommended for most applications[6]. Using a GLCM, texture features such as contrast and energy can be computed[6].

3 Solution

My proposed solution to this problem is to extract spectral and textural features from an image and feed that into a classification algorithm. I determined feature importance via forward selection, eliminating any features which did not contribute to improved model accuracy.

Prior to feature extraction, I resize the source image to 400x400 pixels, which reduces the memory footprint and improves the performance on lower end devices.

The features used by the algorithm are: average NRBR, energy (red), contrast (red), GLCM mean (red), and GLCM standard deviation (red). In addition, a bias of 1 is also used by the classification algorithm. All values are normalized to approximately between 0 and 1 based on the minimum and maximum of the training data.

The average NRBR is just the average NRBR value of all pixels in the image.

To calculate texture features, the image is divided into 100x100 pixel areas, without any overlap. A GLCM is computed for each area using the 16 level red channel. Each matrix is symmetrical, normalized, and direction invariant with a step size of 1. The contrast, energy, mean, and standard deviation is calculated for each GLCM. The average of the contrast, energy, mean, and standard deviation across all 16 GLCMs is taken.

From these features, a logistic regression algorithm was trained using the stochastic gradient descent algorithm. The output of this algorithm is the softmax probability for each of the 10 cloud genera.

The weighted average F1 score is used to evaluate the model performance. On ~300 images, unevenly distributed, the weighted average F1 score was 0.63. This model was included in version 4.6.0 of Trail Sense.

4 Conclusion

This paper gave an overview of a model for cloud image classification that can run offline on mobile devices. I believe with more training data, the accuracy of this model will improve, as some of the classes had only a handful of samples while others had dozens. The proposed algorithm will allow anyone with a smartphone to utilize clouds in offline weather prediction, regardless of experience level.

References

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