Separating Un-Obstructed from Obstructed Images using Google Teachable Machine

FIRE: THE FIRST-YEAR INNOVATION & RESEARCH EXPERIENCE
CLOUD COMPUTING

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Introduction

NASA GLOBE Clouds aims to use civilian-taken images of clouds to train a model that can correctly identify cloud types. In order to have a data set that is valid, reliable, and relevant, it is important that the images taken by civilians are clear and accurately labeled.[1] Without clean data, the output of the model will not be valid.[2] The main objective of our team's project is to create a model that can accurately and precisely distinguish obstructed images from pure clear and cloud images.

Tools & Data

- Google Teachable Machine: A web-based, supervised machine learning model that uses a provided dataset of images.
- NASA GLOBE Cloud: A citizen-scientist-based collection of sky images that are labeled according to cloud type, cloud coverage, and other relevant factors.

Methods

Each member was responsible for going into the GLOBE Clouds dataset and manually choosing images of various cloud types. These images were then separated into four classes based on how much of the sky was obscured in each image. All of the images were resized to be 224x224 so that they wouldn't be modified as they were being used to train the teachable machine.

- Un-Obstructed: No obstructions in the image (clear sky or cloud image).
- Minor Obstructed: 1-25% of the image is obscured.
- Moderate Obstructed: 25-50% of the image is obscured.
- Major Obstructed: More than 50% of the image is obscured.

Figure 1. Left: An image with a Major Obstruction. Right: An image with a Minor Obstruction.

Results

Our sorted data was split into a testing and training set so that we could train a teachable machine. Once our teachable machine was trained, we tested it and made a confusion matrix of our results.

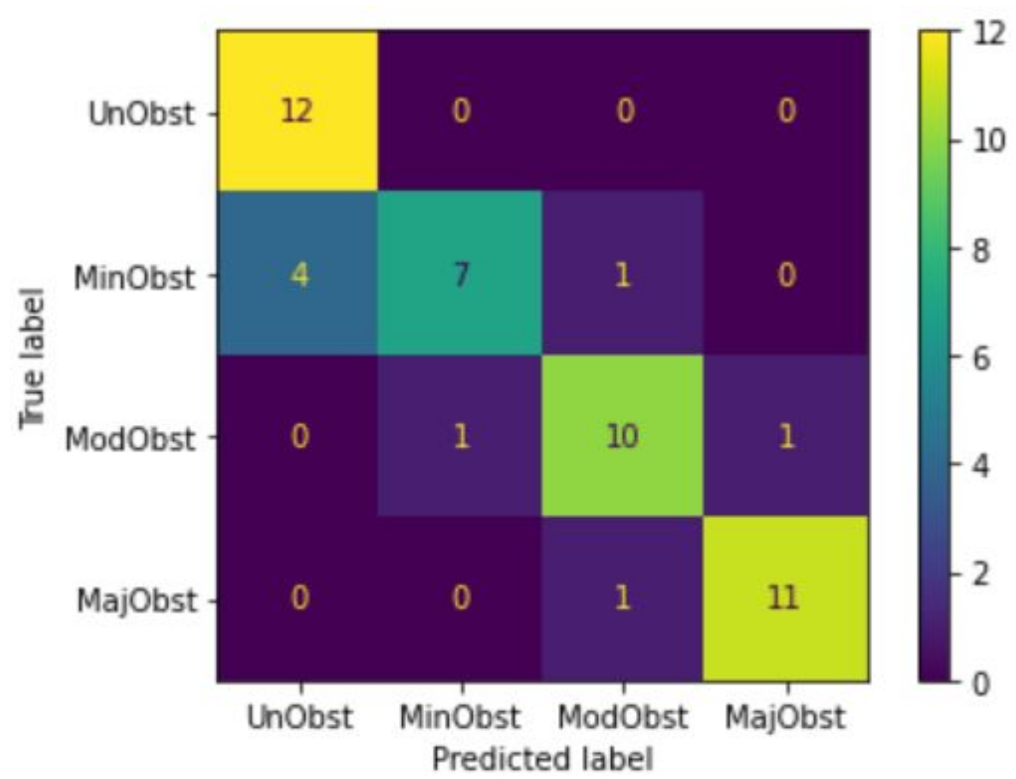

Figure 2. The confusion matrix for our teachable machine model. The model did well at identifying our unobstructed images, but had some trouble distinguishing between minor obstructed images and unobstructed images.

Reading Our Confusion Matrix: the vertical axis represents the actual classification of an image in each category. The horizontal axis represents the model's prediction of an image. Ideally, the predicted value for an image should match its truth value and form a diagonal line of results.

Teachable Machine Performance

- Un-Obstructed Precision: 75%
- Minor Obstructed Precision: 87.5%
- Moderate Obstructed Precision: 83%
- Major Obstructed Precision: 92%
- Overall Accuracy: 83%

Visualizing the Data:
The Minor Obstructed category had the smallest accuracy score, so a visualization (Fig. 3) was made to see what kind of Minor Obstructed images were getting misclassified.

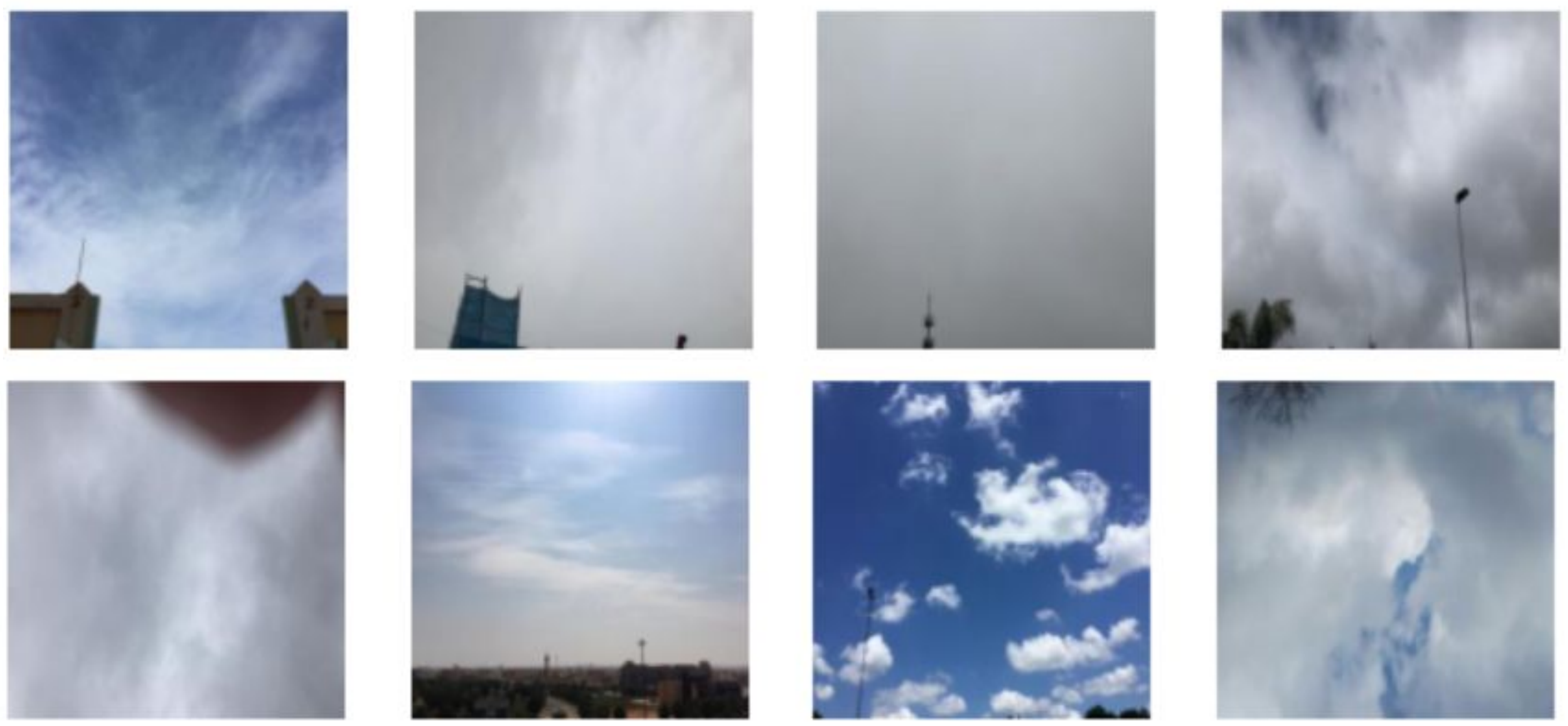

Figure 3. Top Row: Minor Obstructed Images that were correctly classified. Bottom Row: Minor Obstructed images that were incorrectly classified as something else.

Literature

1. Robles, M. C., Amos, H. M., Dodson, J. B., Bouwman, J., Rogerson, T., Bombosch, A., Farmer, L., Burdick, A., Taylor, J., & Chambers, L. H. (2020, August 4). Clouds around the world: How A simple citizen science data challenge became a worldwide success. *American Meteorological Society.* https://doi.org/10.1175/BAMS-D-19-0295.1
2. Chai, C. P. (2020). The importance of data cleaning: Three visualization examples. *Chance*, *33*(1), 4-9. https://doi.org/10.1080/09332480.2020.1726112
3. Bui, H. M., Lech, M., Cheng, E., Neville, K., & Burnett, I. S. (2016). Using grayscale images for object recognition with convolutional-recursive neural network. *IEEE Sixth International Conference on Communications and Electronics (ICCE)* (pp. 321-325). doi: 10.1109/CCE.2016.756265

Discussion

Our main goal was to see if we could develop a model that could accurately and precisely distinguish between heavily obstructed images and images with little to no obstructions. We wanted our model to perform with at least 80% accuracy and in the end it performed with 83% accuracy, so we are satisfied with its performance.

A likely explanation for the poorer performance in the minor obstruction category is the quality of the images themselves. In our comparison of images seen in Fig. 3, a couple of the images contain very small obstructions that are only a few pixels long or wide. Because these obstructions were so small, the teachable machine matched them more closely to unobstructed samples rather than minor obstruction samples that contain larger obstructions. However, in the context of our mission, this is not necessarily a problem. Images that are slightly obstructed are still very much usable, so the model confusing some of the light obstructions with clear/cloud images simply means that it can see the cloud beyond the obstruction.

It should be noted that for our other categories in Fig. 2, specifically moderate and major obstructions, the model did confuse a couple of the images. This is also not a concern, as the line between what constitutes a moderate versus major obstruction was fairly thin. For the purposes of our project, we mainly wanted our model to tell the difference between an image that is usable and an image that is unusable, so we are unconcerned with it confusing moderate and major obstructed images.

Future Work

The focus of our project was to have a model flag obstructed images so that the future NASA Globe Clouds model would only use images that were cleaned. The next step would be to create a model that can both flag and remove heavily obstructed images from the dataset. Another direction future FIRE students could take would be to grayscale the images and see if that would make classifying them easier, as there is research to suggest that grayscaling improves accuracy.[3]