TITAN CLOUD IDENTIFICATION WITH DEEP TRANSFER LEARNING

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ABSTRACT

Despite widespread adoption of deep learning models to address a variety of computational vision tasks, planetary science has yet to see extensive utilization of such tools to address its unique problems. On Titan, a moon of Saturn, tracking seasonal trends and weather patterns of clouds provides crucial insights into one of the most complex climates in the Solar System, yet much of the available image data is still processed manually. We demonstrate that transfer learning techniques can deliver a high degree of accuracy for cloud detection on the data collected from the Cassini–Huygens Mission to Saturn from 1997-2017. We present this work to encourage others to join us in analysis of cloud data throughout the Solar System, as future telescopy projects promise an influx of images in the coming years.

1 INTRODUCTION

Fundamental planetary research into Titan, Saturn's largest moon, indicates the presence of a "methane cycle" analogous to the water cycle on Earth. Denser than any other moon's in the solar system, Titan's atmosphere harbors a dynamic climate capable of supporting complex meteorological phenomena including precipitation, lakes, rivers, and clouds of methane (Brown et al., 2010). Understanding the seasonal and weather patterns of these clouds is essential to developing a model for Titan's atmosphere, which may also lend greater understanding towards the atmospheric mechanisms of other Solar System worlds including the Earth. While most researchers in the field rely on manually combing through images to accumulate data, machine learning models have the potential to quickly analyze Titan image datasets to detect multi-year trends in cloud formation and development. In a white paper for the *NRC Planetary Science and Astrobiology Decadal Survey*, 51 researchers signed a statement emphasizing a pressing need for machine learning in planetary science projects (Azari et al., 2020). Many such projects have large datasets that are processed manually, leaving significant opportunity for the implementation of modern deep learning techniques on Titan and beyond.

In addition to processing data after missions are complete, deep learning models may be beneficial in flight as well. One of the most significant problems facing robotic missions is downlink bandwidth: only so much information can be transmitted back to Earth at a given time. As spacecraft cameras become more advanced, increasingly large images must be compressed and transmitted. Without a means of identifying useful images, a system is forced to store and eventually transmit all of them. This creates a bottleneck that affects missions to every world in the Solar System. If instead onboard models could determine which images are valuable and which to discard before transmitting, then the spacecraft would be able to transmit much more high-quality data.

2 DATASET, EXPERIMENTS, AND RESULTS

2.1 BACKGROUND

Capturing high-quality images of clouds on Titan comes with a host of challenges. The moon's methane-rich atmosphere possesses a haze that is opaque to optical observations, excepting only specific ranges of the infrared spectrum (Turtle et al., 2011). Moreover, the Saturnian year is 29.4 times longer than Earth's. Much like Earth's moon, Titan is tidally locked with Saturn, meaning it always shows the same face to its parent body. Because the Saturnian year, and thus Titan's as

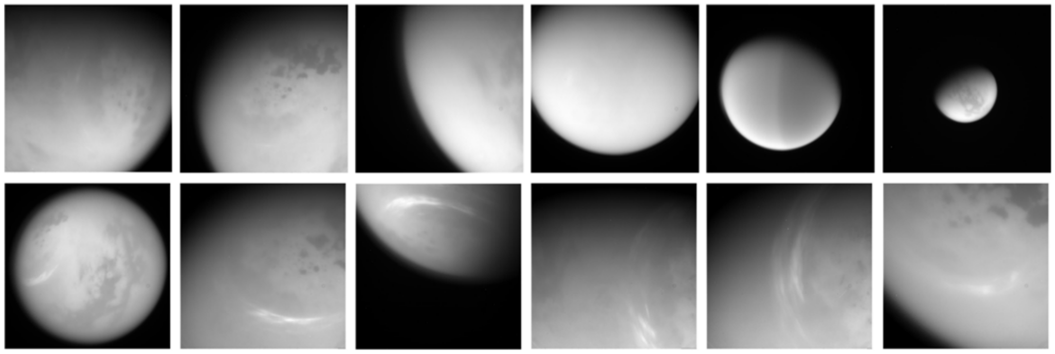

Figure 1: Examples of images in the Cassini dataset

well, is 29.4 Earth-years long, Titan's seasons progress significantly slower than those on Earth (Rodriguez et al., 2009). For this reason, cloud development must be observed over several Earth-decades to get the full picture. This means that the only effective way to capture seasonal progression of clouds on Titan is with a dedicated robotic mission in Saturnian orbit, because it is impractical to dedicate ground-based telescopes to such a long time period. NASA's Cassini mission, which observed the Saturn system from 2004-2017, delivered hundreds of thousands of images of Titan's surface. Cassini's Imaging Science Subsystem (ISS), one of two systems used to collect images, included several infrared filters capable of piercing the methane haze and enabling cloud capture (Porco et al., 2004).

Several factors contribute complexity and difficulty with respect to analyzing Cassini data. Aside from the extensive variety of cloud shapes and sizes, the Cassini images are only black and white with one channel, as evident in Figure 1. Additionally, Cassini's position with respect to Titan varies significantly throughout the course of the mission. While Earth-based satellites orbit at an essentially constant radius, giving images a consistent scale, Cassini followed an orbit around Saturn that brought it between 5,000 km and 5 Mkm from Titan during the mission. This means that the images are captured from erratic angles with disparate lighting conditions and resolutions. We summarize these unique problems as the following: 1. Cloud shape and size variability, 2. Single channel data, 3. Frequent artifacts / noisy images, 4. Cloud-surface contrast, 5. Cassini positioning.

To our knowledge, our work is the first to implement deep learning computer vision models for the purpose of Titan cloud image processing. We implement a binary classification model trained via transfer learning for identifying whether or not a Cassini image of Titan contains one or more cloud formations. This discrimination is essential for determining the presence of clouds over an extended time period, which is a topic of much interest for Titan studies (Turtle et al., 2018) (et al., 2010). We envision a pipeline for easily processing images from future missions to Titan and other moons and planets, and we strive to establish the feasibility of machine learning and transfer learning in planetary science.

2.2 Related Work

Research on Earth can provide insights into cloud detection approaches on other worlds. The vast majority of cloud identification research focuses on terrestrial applications due to relevance to human society and multitudinous high-quality data sources. Before the popularization of deep learning, classic approaches like handcrafted feature representations saw moderate success. While capable in some cases, these models lacked robustness, a substantial drawback given the wide variety of cloud formations possible on Earth (Mahajan & Fataniya, 2020)(Li et al., 2021).

Some deep learning approaches have even become advanced enough to target specific cloud formations. In their work, Liles et al. develop a U-Net model for detecting Above Anvil Cirrus Plume (AACP) formations, a reliable predictor of severe weather (Liles et al., 2020). These significant strides in cloud detection are possible because of the vast quantities of image data available through several satellites orbiting the Earth, enabling the full capabilities of deep learning. Other worlds beyond the Earth do not share the same benefits, making similar approaches more difficult.

Few attempts have been made to automatically detect clouds on Titan. While other works mention computerized cloud detection (e.g. (Turtle et al., 2018)), the only dedicated example in the literature involves using a Bayesian Source Separation algorithm paired with Markov Chain and Monte Carlo simulation methods (et al., 2010). There is considerable room for improvement in this method given the explosion of deep learning results in the last decade.

2.3 Training Procedure

The Cassini data is publicly available via NASA's Solar System Archive and the Jet Propulsion Laboratory's Planetary Data System. We use an initial dataset captured by Cassini's Imaging Science Subsystem (ISS) from June 2004 to October 2017, the full length of the Titan viewing window. In order to narrow this set further, we only keep the 20,000 images from the ISS's CB3 infrared filter. Each image is 1024x1024 pixels with a single grayscale channel. This filter operates at 938nm, which is viable for piercing the thick methane haze of Titan's atmosphere. At this frequency, clouds stand out as white streaks against the surface of Titan, though their visibility still varies widely.

Prior work has also shown that clouds are not dispersed evenly throughout the mission window, but rather appear in high densities during specific months (Turtle et al., 2011). We select a window of November 2015 to October 2017 in order to capture one of these high-density periods, from which we select 320 total images. These images are a representative sample of the wide variety of cloud types and image conditions in the Cassini data. Note that starting from 20,000 images and ending with a set of 320 is symptomatic of the quality of images taken by Cassini, and also their redundancy. Often, dozens of images will show the same cloud formation, diminishing their usefulness for model training. Rather than use as many images as possible, we focus on a high-quality sample that reflects an expert curated view of Titan clouds for our first analysis. Further, using a smaller quantity serves as a better proof of concept for cloud detection on worlds other than Titan, which may not benefit from an extended mission such as Cassini.

Rather than train a new convolutional neural network from scratch, we utilize transfer learning. We adapt VGG-16 (Simonyan & Zisserman, 2015) by adding two more dense layers, one for feature representation and one for output. We also add a dropout layer with a dropout probability of 0.4 to prevent overfitting, and a sigmoid activation function. We then train only the final convolutional layer and our dense layers to adapt VGG-16 to our Titan cloud dataset. We implement our model architecture using Keras with a Tensorflow 2.1 backend running in a Google Cloud Platform environment on a Tesla T4 GPU. Before training, the images are padded with two empty channels to expand their dimensions from single-channel grayscale images to three-channel "RGB" images. We also reduce each image from its original 1024x1024 resolution to 224x224. We apply rotations in a range of 30 degrees and horizontal/vertical flips at random to the images. We also randomly apply horizontal and vertical shifts of up to ten percent of the image size to random images. We use the Adam optimizer with a learning rate of 3e-5, and binary crossentropy for our loss function. Instead of batching the data, we find that a stochastic gradient descent approach is most effective. We train on the entire training set for each epoch, until the model converges and the loss no longer decreases.

2.4 Evaluation Metrics

After training, we evaluate the model with several metrics. We use four values to gauge various aspects of model performance: accuracy, precision, recall, and $F1$ score. We achieve an overall accuracy of 0.95, a precision of 0.9823, a recall of 0.9167, and an $F1$ score of 0.9484.

As discussed previously, clouds on Titan persist for long periods of time. Cassini captured images at a rate such that many images are nearly identical. The high degree of correlation between images poses problems for simple evaluation of precision and recall. Researchers confronted with tens of thousands of potential images may wish to rapidly identify images with high likelihood of clouds and be less concerned with a lower recall rate. Additionally, as many images may be very similar, if the false negatives are grouped according to separate single approaches of the spacecraft, then only a single true positive for each is required for standard scientific inquiry.

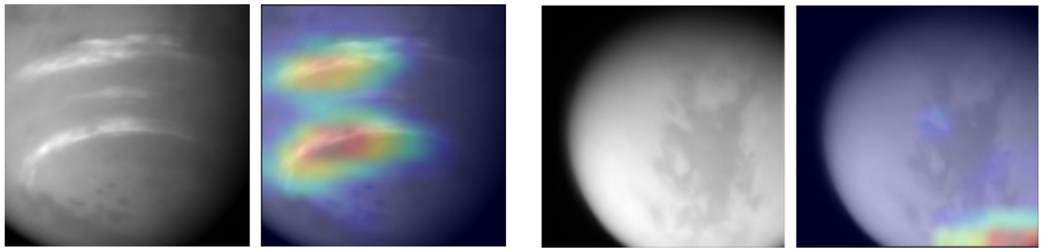

Figure 2: Left: GradCAM heatmap in image with cloud. Right: GradCAM heatmap in image without cloud.

2.5 GradCAM

To make our models more accessible to planetary scientists without a formal deep learning background, we include model evaluation using Gradient-weighted Class Activation Mapping (GradCAM). GradCAM computes a heat map associated with the gradients flowing into the final layer of the CNN in order to visualize areas of high significance to model prediction (Selvaraju et al., 2017). Qualitatively, it illustrates which regions of each image the model deems most important to its classification. See Figure 2 for examples. In our case, the images with GradCAM in Figure 2 show that the model is correctly identifying the cloudy regions in ”cloud” images. In images without clouds, we see GradCAM indicate emphasis on the corners of the image.

2.6 Discussion

Our results indicate that cloud identification from images of Titan from the Cassini mission is tractable. Transfer learning allows us to swiftly train our models in a handful of epochs with a small sample set of data. Importantly it requires only a small number (i.e., low 100's) of hand labeled data points before it is ready for applications across potentially thousands of images. In general this is an advantage in planetary research where quality and quantity of images is not assured due to data collection limitations. Note that while we had the luxury of curating an ideal dataset from a large pool of images, other projects with other worlds do not have such a wealth of data available. The effectiveness of our approach, with limited data and computational resources, should indicate to future researchers that there are opportunities for scientists to address fundamental and important scientific questions related to planetary research with considerable limitations.

3 Future Work

We anticipate an influx of Titan image data due to several key endeavors in the coming decade. The recently-launched James Webb Space Telescope (JWST) possesses an angular resolution of 0.1 arc-seconds, which will be capable of capturing images of Titan at low resolutions. Furthermore, several ground-based telescope projects are in development, including the European Space Agency's Extremely Large Telescope (ELT), which will be completed in 2027, and potentially the Thirty Meter Telescope (TMT) in Hawaii. With 25-39m apertures, these observatories will possess a resolving power capable of capturing images comparable to Cassini in quality, up to 200x200 pixels. This will significantly increase the availability of cloud data on Titan and other worlds.

Our work focuses on evaluating the broad method of transfer learning as an effective method for planetary science. Identifying images with clouds is only the first step in extracting the wealth of atmospheric data available. Future applications of deep learning in this space may involve semantic segmentation for identifying clouds and extracting specific metrics including centroid latitude and area. The barriers to entry for machine learning researchers to find scientifically relevant planetary problems are high, and we hope our evaluation encourages others from the machine learning community to engage with planetary scientists to address important problems.

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