CloudicAI - Mission Space Lab Phase 4

Team name: DeepTeam

Chosen theme: Life on Earth

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1. Introduction

When gazing into the sky, there's one thing that's hard to miss - the clouds. They come in all shapes and sizes and when looking at them, we tend to interpret them as all sorts of objects, be it tools, animals or even people. This quirk of human nature is known as the pareidolia effect. Inspired by it, we want to investigate if one can replicate it with images from space and weather artificial intelligence can be trained to experience it as well. For a more scientific implication of AI image analysis, we further aim to use AI to also classify the clouds scientifically. The reliable classification of clouds is for example central to the quality of weather forecasting and early warning systems, and subject to current research.

Considering cloud detection and classification are both rather difficult problems, especially when limited to visual imagery, we don't expect to get perfect results. We are however confident that we will be able to detect and classify at least some clouds. For the artificial pareidolia effect, we hope to be able to identify the cloud as an object from a range of pre-trained objects.

2. Method

For our experiment, we collect visual data using the camera of the Astro Pi. Our program uses multiple threads to simultaneously take images of the earth and processes them. To save on disk storage, the program automatically discards night images and performs cloud detection in order to remove the background. The cloud detection AI utilizes an autoencoder model, which significantly outperforms the U-Net-Model architecture which we originally employed.

Apart from the detection, the analysis is performed on the ground using Cloudic AI – our image analysis pipeline. For the scientific examination of the clouds, our program first separates the identified clouds and then analyses their features, like transparency and size, individually. Based on the result of the analysis, it then classifies the cloud. Instead of using a clustering algorithm for this task, we compare the properties to predefined cloud types, which limits the variety of classified clouds, but ensures a high performance. For the artificial pareidolia effect, we used the MPEG-7 dataset to train a neural network on Teachable Machine. In a next step, we compare the AI predictions to our own imagination and a survey which we ran at the science fare of our school.

3. Experiment results

The program on the ISS finished after two and a half hours, having taken almost 1500 images, using about 1 GB. As seen in the extensive logs, the program run without any errors and succeeded in its task to deliver the masked clouds to earth.

3.1 Cloud Detection

The cloud detection worked surprisingly well for most images. As seen in figure 1, the clouds are well cut out, with little surroundings left in, and, as deduced from the borders of the clouds just seen on the images, little left out. There were some problems with specific types of ground. Snow for example is even to humans hardly distinguishable from some cloud types (figure 2), and was sometimes included. Different lighting conditions did not seem to affect the cloud detection much.

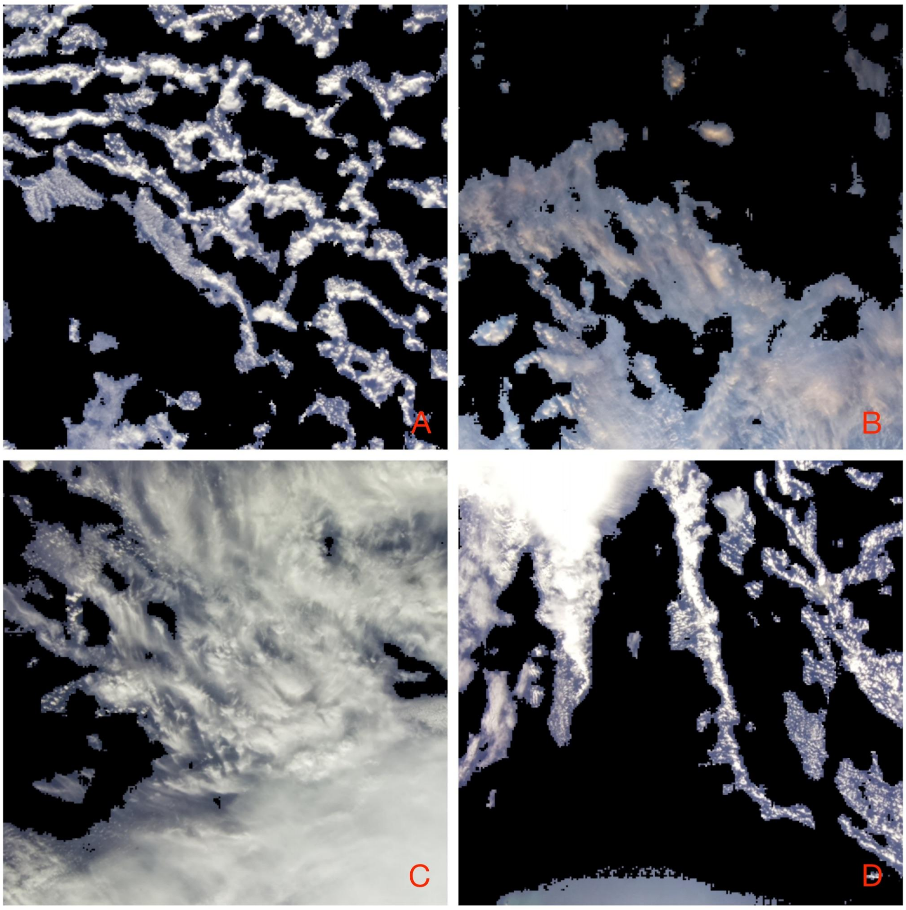

Figure 1: Results of cloud detection

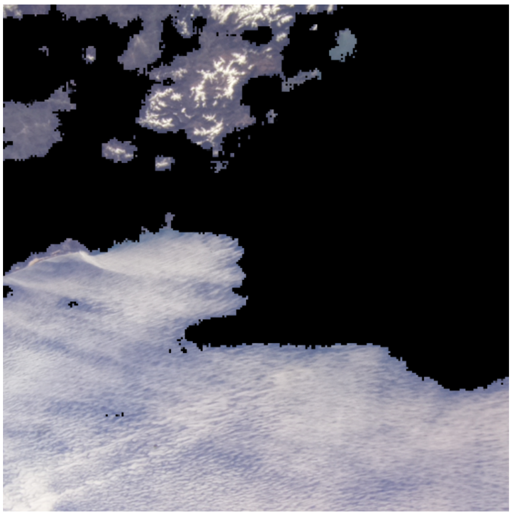

Figure 2: Misclassification of snow

3.2 Cloud Classification

The cloud classification, as one major part of our research, showed overall positive results. Many classifications showed similar results when compared to professional analysis by the [University of Wisconsin–Madison](). As one can hardly tell the height of a cloud from above, this was one of the major difficulties when distinguishing between different cloud types.

High level: Genus cirrus	0.203068
High level: Genus cirrocumulus	0.053961
High level: Genus cirrostratus	0.010928
Mid level: Genus altocumulus	0.217736
Towering vertical: Genus cumulonimbus	0.162742
Towering vertical: Genus cumulus	0.226976
moderate vertical: Genus nimbostratus	0.053961
Low level: Genus stratocumulus	0.066136
Low level: Genus stratus	0.004492

Figure 3: Classification results for cloud A (figure 3)

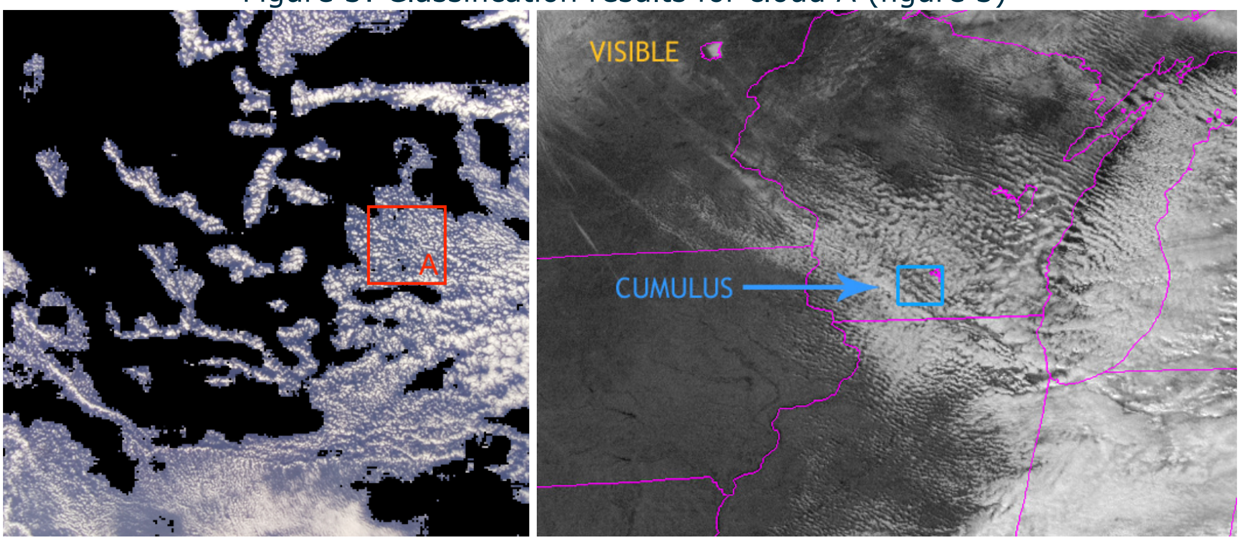

Figure 4: Left: CloudicAI image (Cumulus, Correct), Right: Professional classification by [University of Wisconsin–Madison](#) (Cumulus)

```
High level: Genus cirrus                  0.030469
High level: Genus cirrocumulus            0.058941
High level: Genus cirrostratus            0.020029
Mid level: Genus altocumulus              0.237633
Towering vertical: Genus cumulonimbus     0.253743
Towering vertical: Genus cumulus          0.074180
moderate vertical: Genus nimbostratus     0.134962
Low level: Genus stratocumulus            0.085151
Low level: Genus stratus                  0.104891
```

Figure 5: Classification results for cloud B (figure 6)

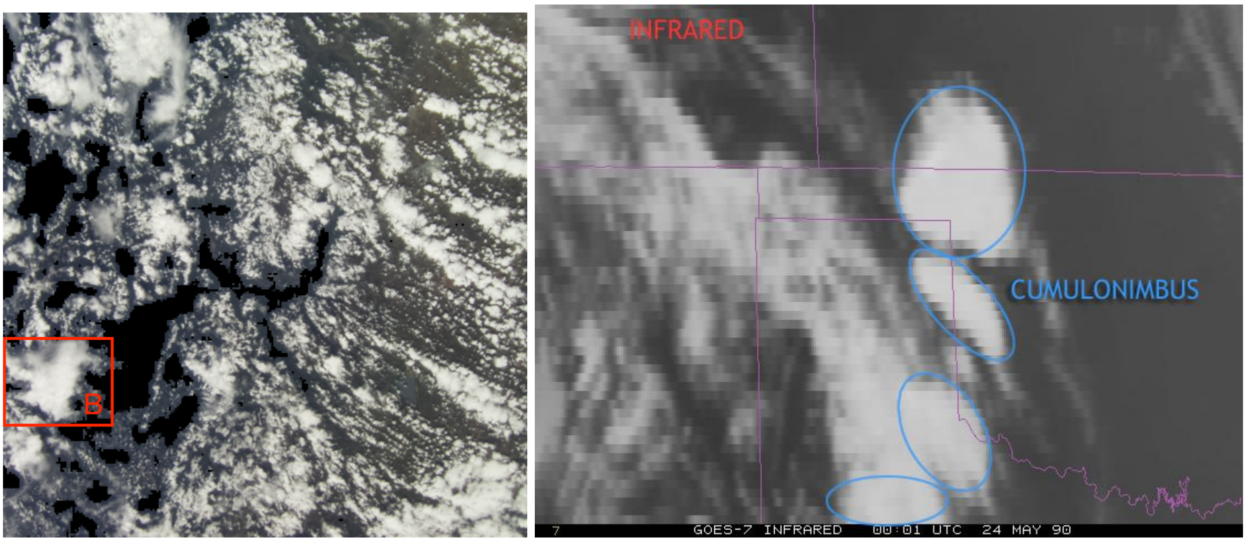

Figure 6: Left: CloudicAI image (Cumulonimbus, Correct), Right: Professional classification by [University of Wisconsin–Madison](#) (Cumulonimbus)

High level: Genus cirrus	0.082604
High level: Genus cirrocumulus	0.125695
High level: Genus cirrostratus	0.043654
Mid level: Genus altocumulus	0.086660
Towering vertical: Genus cumulonimbus	0.115779
Towering vertical: Genus cumulus	0.113559
moderate vertical: Genus nimbostratus	0.081730
Low level: Genus stratocumulus	0.158847
Low level: Genus stratus	0.191467

Figure 7: Classification results for cloud C (fig. 8)

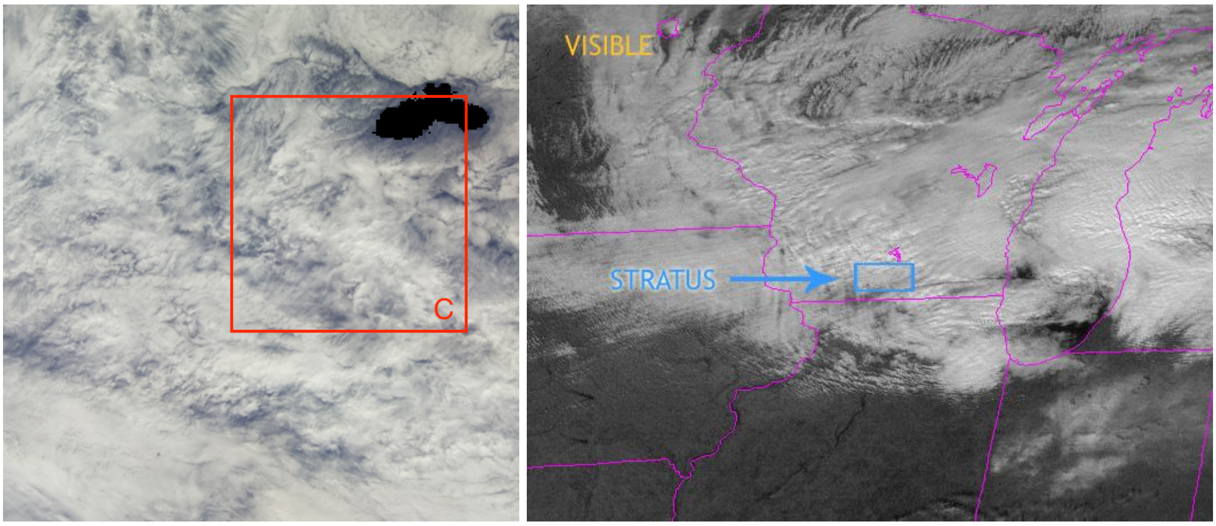

Figure 8: Left: CloudicAI image (Stratus; Correct), Right: Professional classification by University of Wisconsin–Madison (Stratus)

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High level: Genus cirrus                  0.090320
High level: Genus cirrocumulus            0.122700
High level: Genus cirrostratus            0.127188
Mid level: Genus altocumulus              0.012465
Towering vertical: Genus cumulonimbus     0.133169
Towering vertical: Genus cumulus          0.078106
moderate vertical: Genus nimbostratus     0.180368
Low level: Genus stratocumulus            0.117548
Low level: Genus stratus                  0.138132
```

Figure 9: Classification results for cloud C (fig. 10)

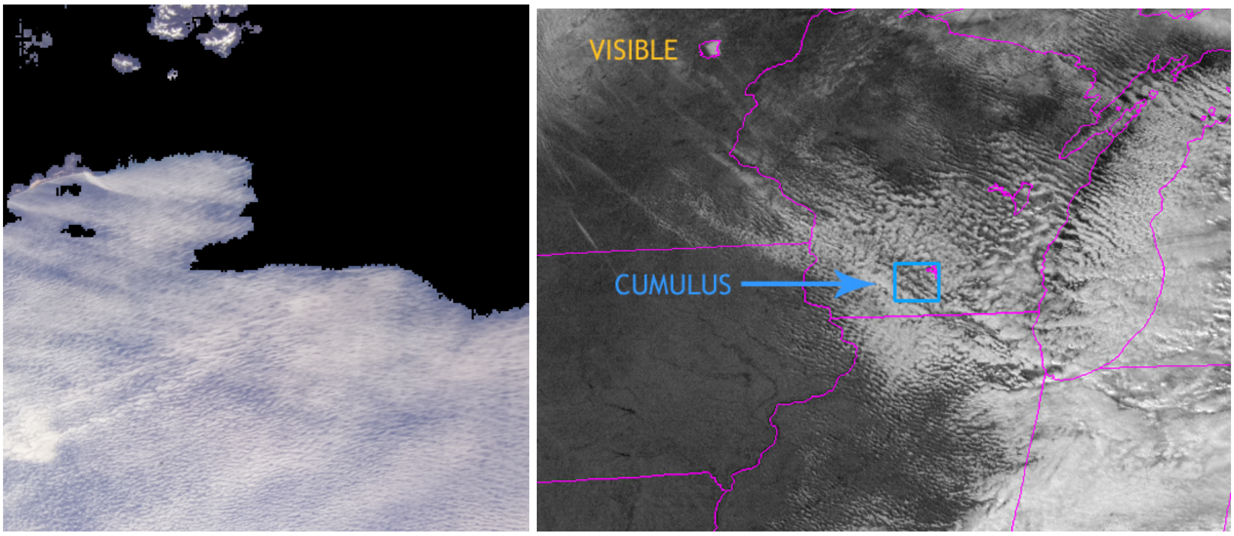

Figure 10: Left: CloudicAI image (Stratus; Wrong) Right: Professional classification by University of Wisconsin–Madison (Cumulus)

3.3 Paraidolia

When comparing the pareidolia results from our AI with our survey, we find that for some images the impressions match closely (figure 9, image D), while showing no similarities for others (image A). As we also allowed custom answers in addition to the objects our AI used in the survey, we can see that humans interpret far more complex scenes in the clouds than our AI (“fire-breathing shopping trolley”, image A). This discrepancy results from the fact that our AI has a limited set of possible output values. It is interesting to note that the AI interpretations seem mostly plausible to humans, even though in contrast to humans the AI does not care about the orientation of the shapes.

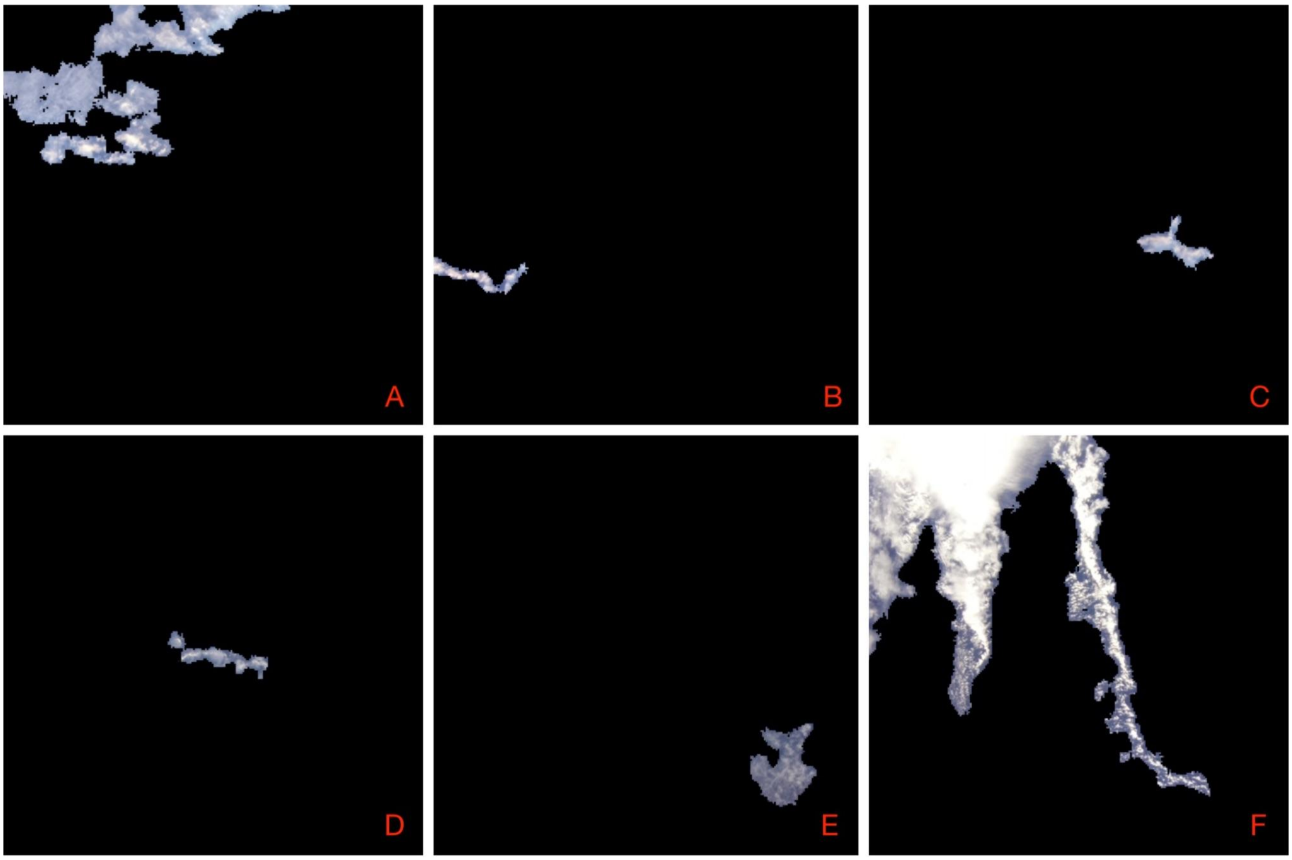

Figure 11: Pareidolia images

4. Learnings

During our project, we encountered several challenges. Detecting clouds for example proved to be more difficult than anticipated, especially distinguishing between clouds and other bright areas, like snow. To overcome this, we had to rework our AI, switching from a U-Net Model to an Autoencoder. We also found that cropping the image to hide the window drastically improves the AI's performance. Still, our AI has limitations, especially when it comes to segmenting clouds which are close together or overlap.

Regarding the program we ran on the ISS, we were overcautious with the disk space and execution time. We could easily have let our experiment last 20 to 25 minutes longer and have it save the original images as well, which would have made it easier to evaluate the accuracy of the cloud detection model.

But beyond developing machine learning models and coding, working as a team was a valuable experience. We were effective at planning and organizing our project and worked together effectively. We divided tasks based on individual strengths, assigned clear responsibilities and maintained active communication. Only time management was a slight issue, signified by the last minute submission of our report.

5. Conclusion

To summarize, our project aimed to investigate the pareidolia effect in clouds and use AI for cloud analysis. While we faced several challenges, we successfully developed AIs to detect and classify clouds. There are limitations to our method, like the segmentation and classification of closely spaced clouds, but overall we are very proud of the results. As far as the artificial pareidolia effect goes, we were surprised to find, that the AI 'perception' wasn't too different from the perception of humans. Unsurprisingly however, the free interpretation of humans is still far more complex than the simple shape detection by the AI.

Apart from the technological achievements, we worked great as a team and learned a lot about a multitude of technologies.

In the future, we plan to enhance our detection AI with more training data and to increase the number of objects recognized by the pareidolia AI. Further, we want to extend the analysis and for example be able to tell the wind direction from the shape of the clouds.

Overall, we believe our project serves as a promising step towards advancing AI capabilities in cloud analysis and understanding not only pareidolia but generally the similarities between human and artificial intelligence.