Semantic Segmentation with Deep Convolutional Neural Networks for Automated Dust Detection in Goes-R Satellite Imagery

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Abstract

Airborne dust, including Dust storms and weaker dust traces, can have deleterious and hazardous effects on human health, agriculture, solar power generation, and aviation. Although earth observing satellites are extremely useful in monitoring dust using visible and infrared imagery, dust is often difficult to visually identify in single band imagery due to its similarities to clouds, smoke, and underlying surfaces. Furthermore, night-time dust detection is a particularly difficult problem, since radiative properties of dust mimic those of the cooling, underlying surface. The creation of false-color red-green-blue (RGB) composite imagery, specifically the EUMETSAT Dust RGB, was designed to enhance dust detection through the combination of single bands and band differences into a single composite image. However, dust is still often difficult to identify in night-time imagery even by experts. We developed a Deep Learning, UNET image segmentation model to identify airborne dust at night leveraging six GOES-16 infrared bands, with a focus on infrared and water vapor bands.The UNET model architecture is an encoder-decoder Convolutional Neural Network that does not require large amounts of training data, localizes and contextualized image data for precise segmentation, and provides fast training time for high accuracy pixel level prediction. This presentation highlights collection of the training database, development of the model, and preliminary model validation. With further model development, validation, and testing in a real-time context, probability-based dust prediction could alert weather forecasters, emergency managers, and citizens to the location and extent of impending dust storms.

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Deep Convolutional Neural Networks for Automated Dust Detection

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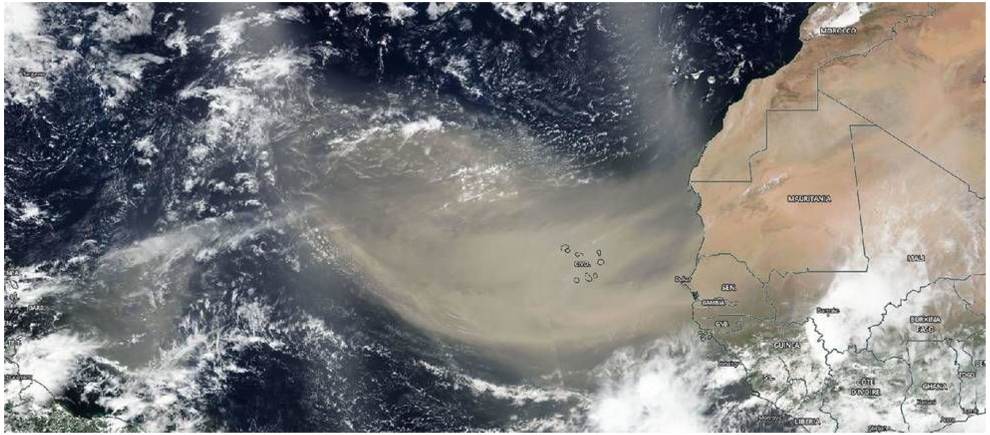
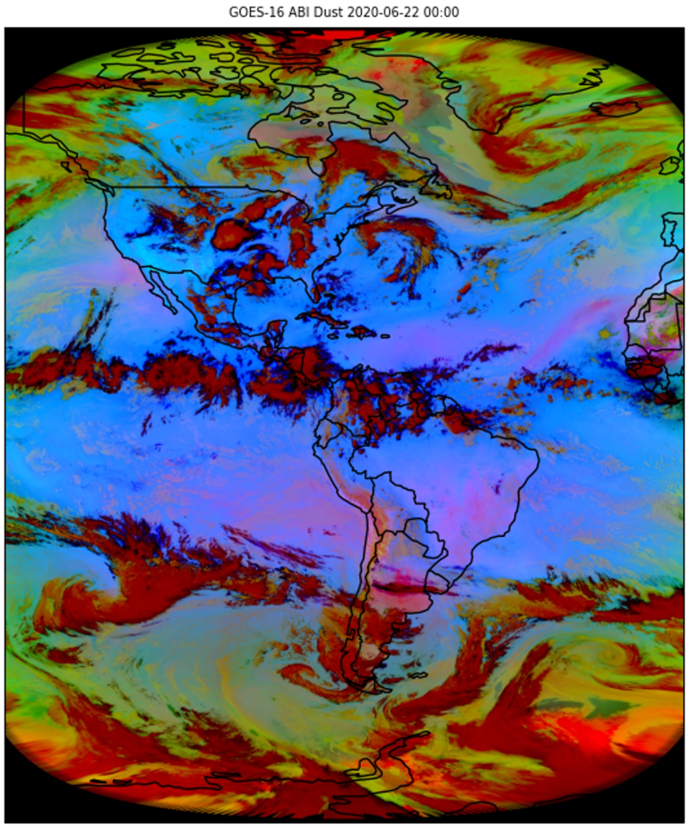
Dust Storms can have many harmful effects on the world

[6]

Detecting Dust Storms is both difficult and time consuming



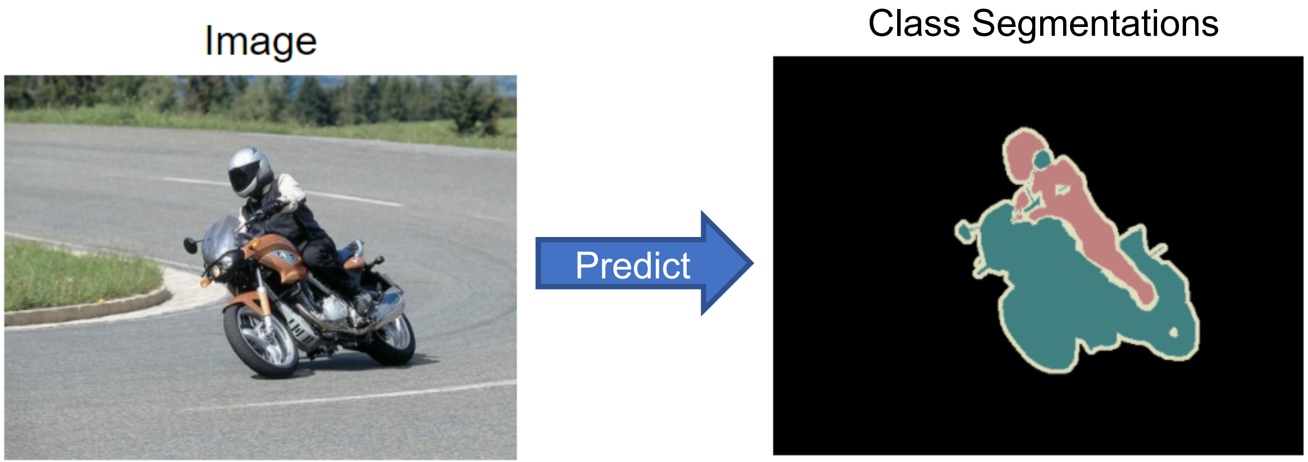
[5]



Method

- Deep Learning based semantic image segmentation model (UNET)
- Six GOES-16 bands, with a focus on infrared and water vapor bands.
- Automatically identifies airborne dust at night

Deep Learning can be leveraged in order to segment out objects within an image (A.K.A. Semantic Segmentation)



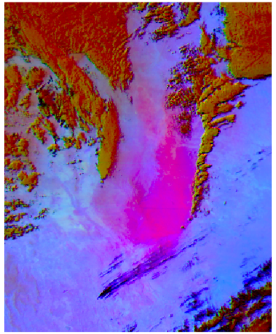
[4].

Dust Storm labels are handcrafted by experts and learned by the model

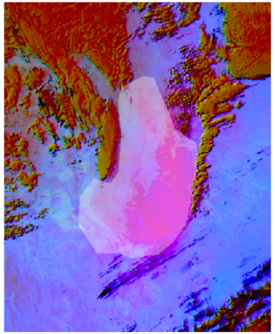
RGB Interpretation

1. **Dust plume** *(magenta, pink)*
2. **Low, warm water cloud, or thick dust** *(light purple)*
3. **Desert surface (day)** *(light blue)*
4. **Mid, thick clouds** *(tan shades)*
5. **Mid, thin cloud** *(green)*
6. **Cold, thick clouds** *(red)*
7. **High, thin ice clouds** *(black)*
8. **Very thin cloud (Over warm surface)** *(blue)*

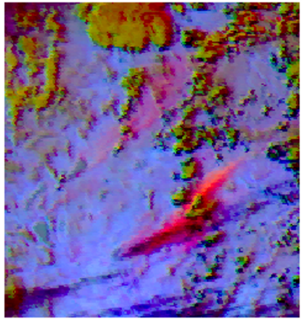
RGB Satellite Data



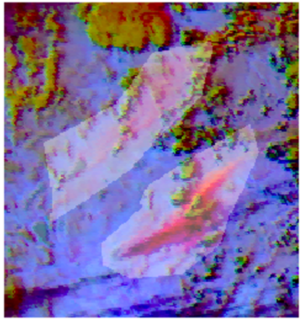
RGB With Dust Labeling



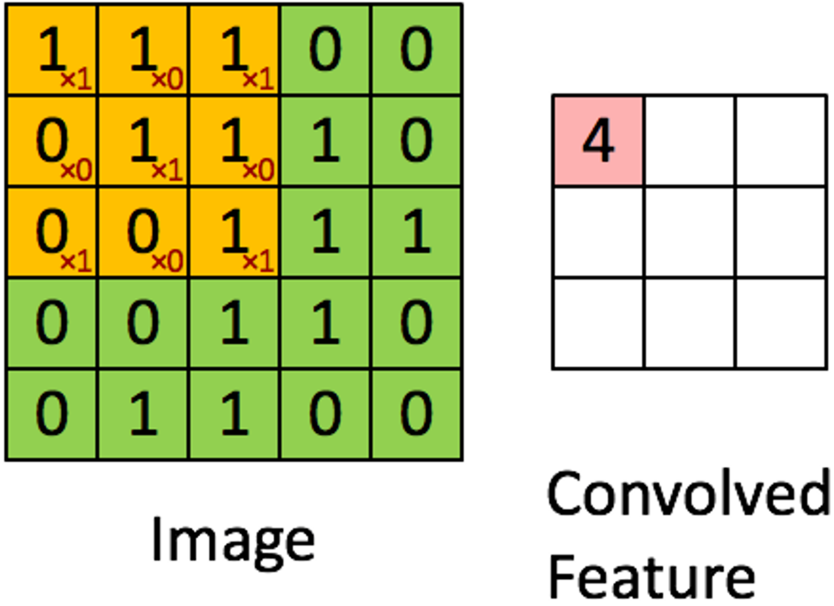
RGB Satellite Data



RGB With Dust Labeling



Convolutional Neural Networks can be leveraged to learn the features within an image irrespective of Spatial and temporal dependencies.

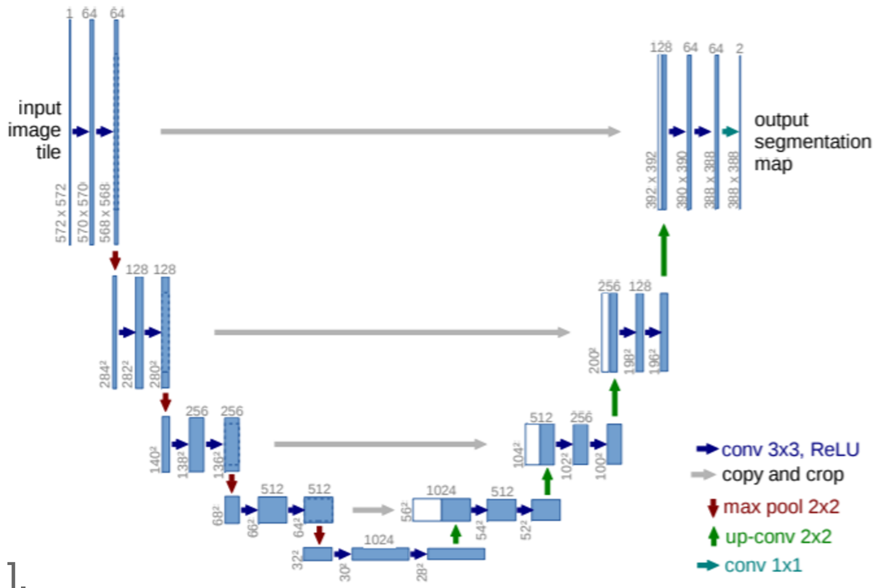


Kernel/Filter, K =

1	0	1
0	1	0
1	0	1

[7].

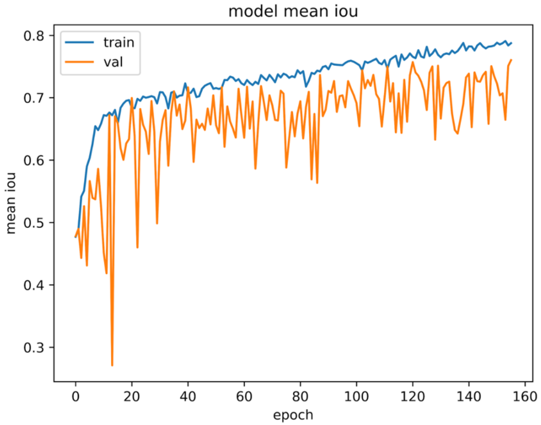
UNET Architecture

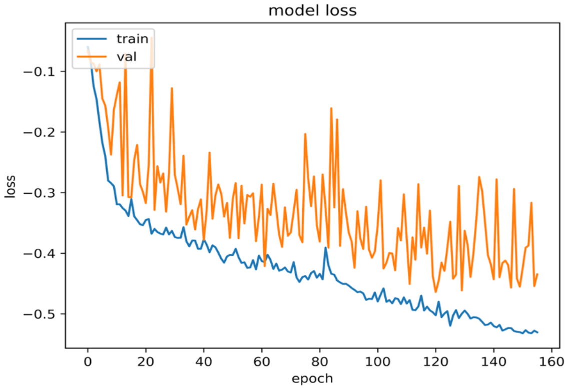


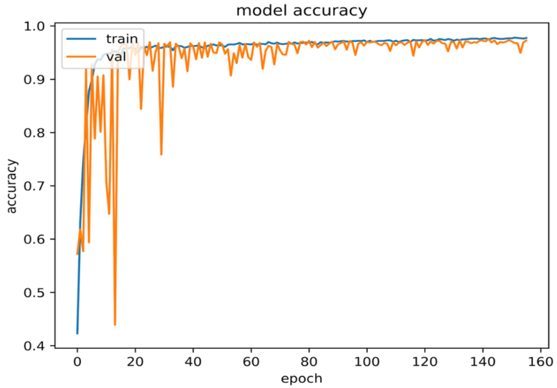
[1].

- Convolutional Encoder-Decoder Network
- Learns low level features using Convolution
- Maps to high level (i.e. Dust Storms)
- Scales image back and creates segmentation
- Python, TensorFlow, Keras implementation.

Training Results







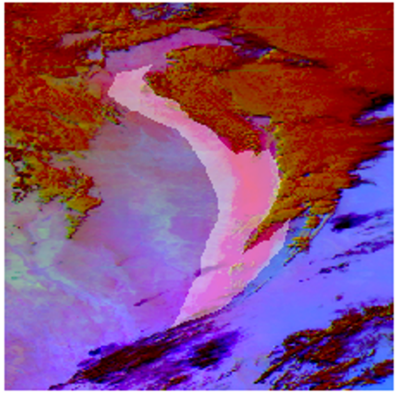
Model IOU:
Important for Semantic Segmentation.
Overlap of predictions to Labels.
Higher IOU means closer predictions to labels.

Model Loss:
Most important metric.
Want to minimize loss
So that the model learns.

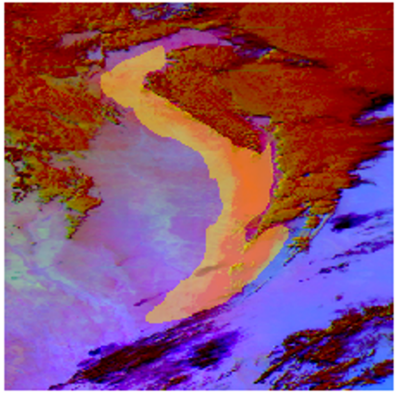
Model Accuracy:
Number of Correct predictions
Out of total predictions.
Pixel level.
Want to get as close to 1 as possible.

The UNET performed well for most cases

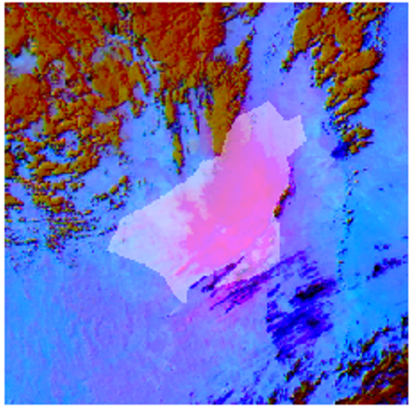
Labels



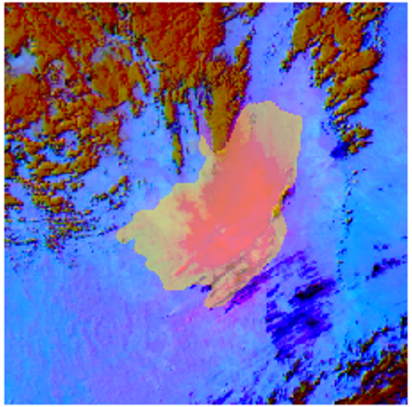
Model Predictions



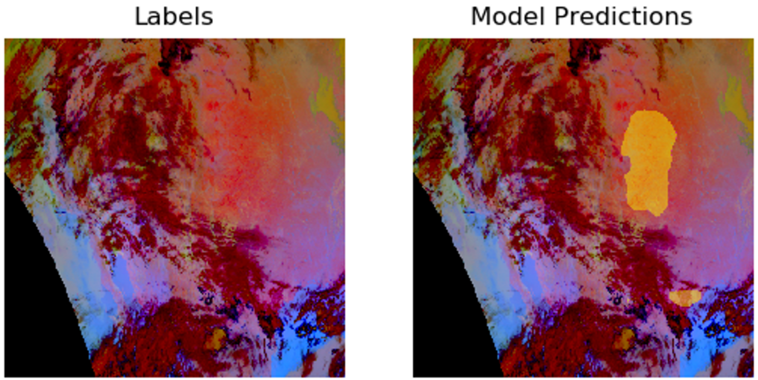
Labels

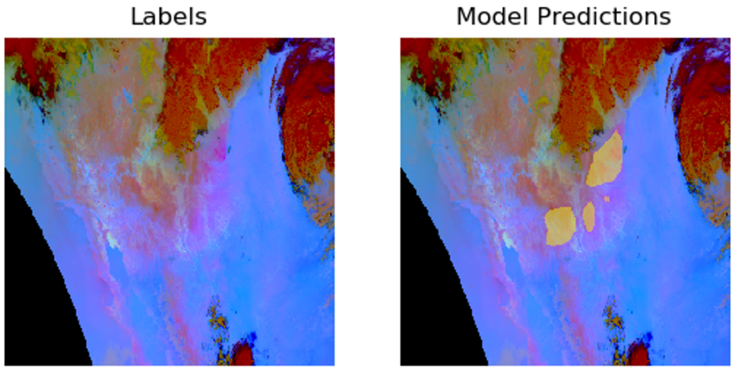


Model Predictions



Some cases of poor predictions did arise





Model Predicts poorly in some cases. Left images do not have any dust; the predictions made are on the underlying surface that has similar IR characteristics as dust. Right Image has smoke and a similar underlying surface.

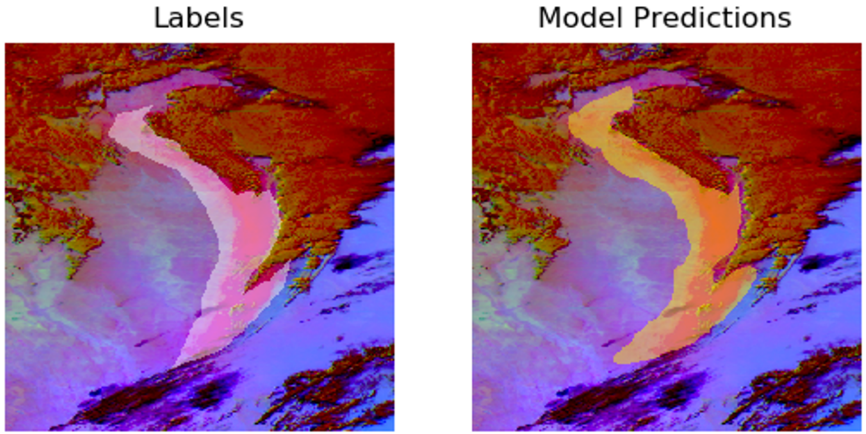
Test Metrics

Accuracy	0.975
Precision	0.729
F1_score	0.747
Recall	0.766
Mean IOU	0.530
Roc Auc	0.882

- High accuracy is good.
- Precision shows signs of over classification
- Mean IOU could improve.
- Likely caused by noisy labelling and/or Difficult cases to identify dust in.

Conclusion

With further model development, validation, and testing in a more representative context, Deep Learning based dust storm prediction could alert weather forecasters, emergency managers, and citizens to the location and extent of impending dust storms much quicker than before.



Dataset Creation
Semantic Segmentation
Statistical Validation

Automated Dust Detection

Feel Free to contact reach out below if there are any questions about our work!

Email: Talha0128@gmail.com

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