# Improving satellite-based hotspot detection through deep learning-enabled smoke recognition

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AGU NH41A: Transforming Natural Hazard Monitoring and Understanding: Advances in Artificial Intelligence and Earth Observation Technologies

# Motivation

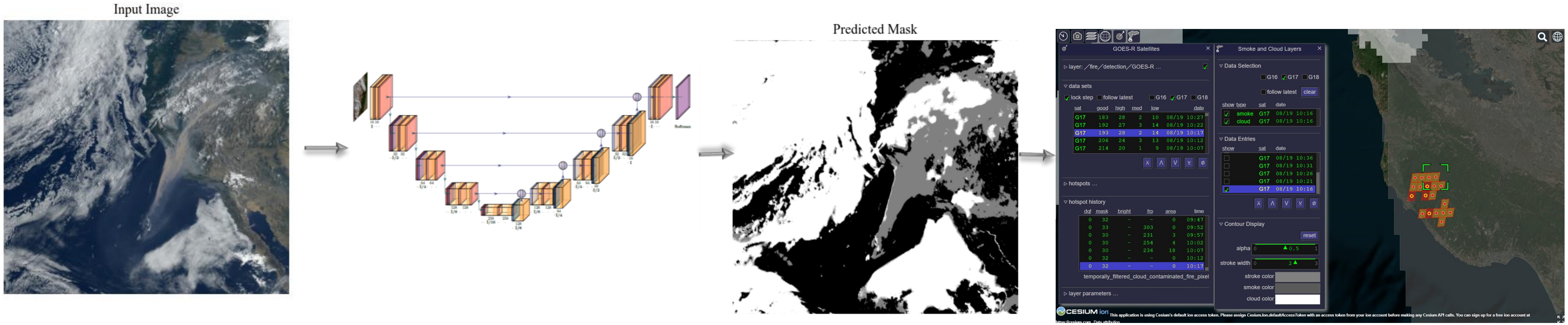
- Wildfires have been increasing in size and destruction in recent years
- Timely hotspot detection is necessary, yet existing satellites have high false negative and false positive rates
- One cause of false negative detection is “cloud-contamination”
- We build a model to recognize smoke from cloud

Fig 1: Examples of wildfire smoke and clouds from satellites

# Method

- **Architecture:** U-net vs ResNet segmentation model
- **Pretraining**: train on domain-specific images using self-supervised learning
- **Fine-tuning:** train on labeled data using supervised learning
- **Implementation**: the model is deployed in a real-time web-based application using microservices

Fig 2: Model implementation flowchart



# Smoke Segmentation Model: Architecture

- Encoder-decoder architectures are commonly used for segmentation tasks
- Large pre-trained models (e.g. SAM) are challenging for time and resource constrained applications
- ResNets generally outperform U-nets, but are costly

Fig 3: U-net architecture

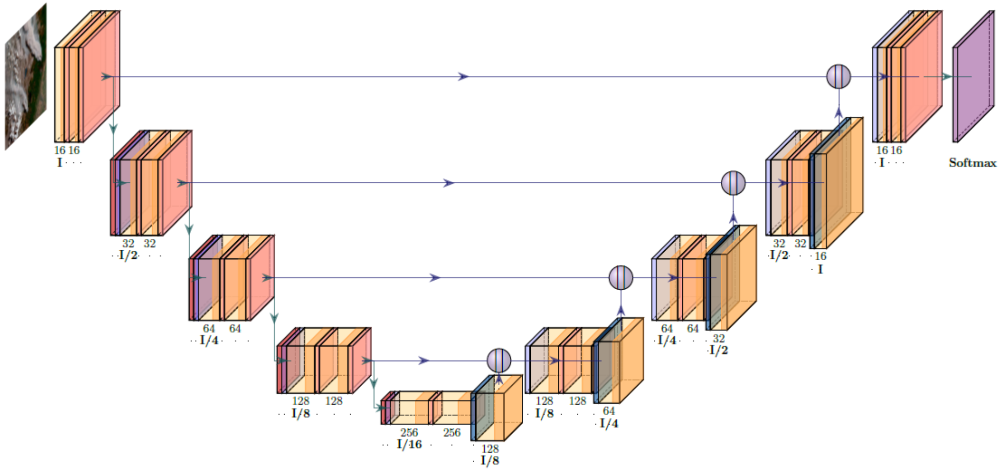
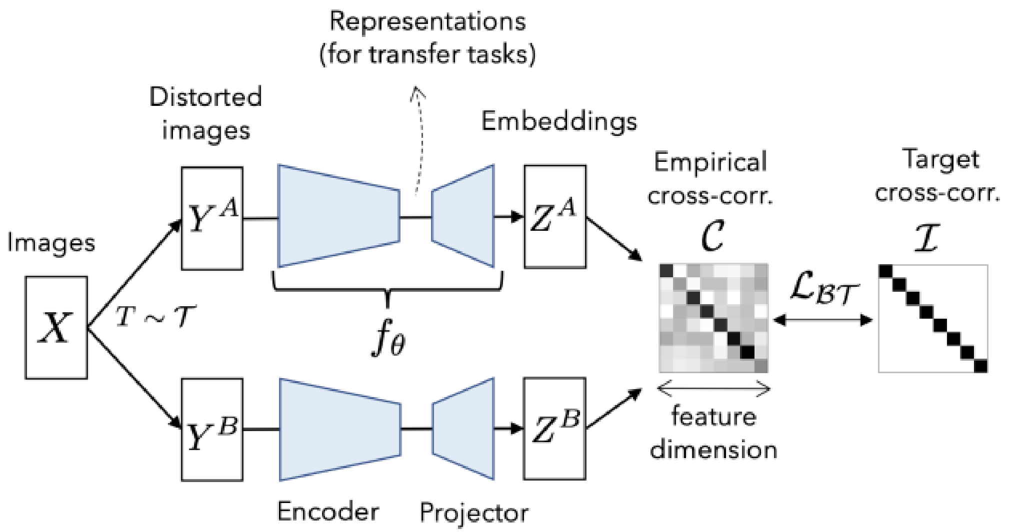



Table 1: Model size comparison

| Model | Parameters |
|---|---|
| Segment Anything Model | 632 million (encoder) |
| Our ResNet | 32 million |
| Our U-Net | 2 million |

# Smoke Segmentation Model: Pre-training

- Self-supervised learning - **Barlow Twins**:
  - Inputs two distorted images into twin U-net or ResNet encoders
  - Calculates loss as difference between cross-correlation and identity matrix
  - Extract one twin for model backbone
- Pre-training on ~10,000 unlabeled GOES-R satellite images
- Warm-up period for optimizer
- Early stopping: max of 25 epochs, finished at 9 epochs for U-net and 24 for Resnet




Zbontar, J., Jing, L., Misra, I., LeCun, Y., Deny, S., 2021. Barlow twins: Self-supervised learning via redundancy reduction, in: International Conference on Machine Learning, PMLR. pp. 12310–12320.

# Smoke Segmentation Model: Fine-Tuning

- 150 labeled images split into:
  - 125 training/validation set for design optimization using 5-fold cross-validation
  - 25 in test set for final model evaluation
- 2x4 design:
  - Model: U-net vs ResNet
  - Training: Vanilla vs data augmented vs BT transfer learning vs BT fine-tuning

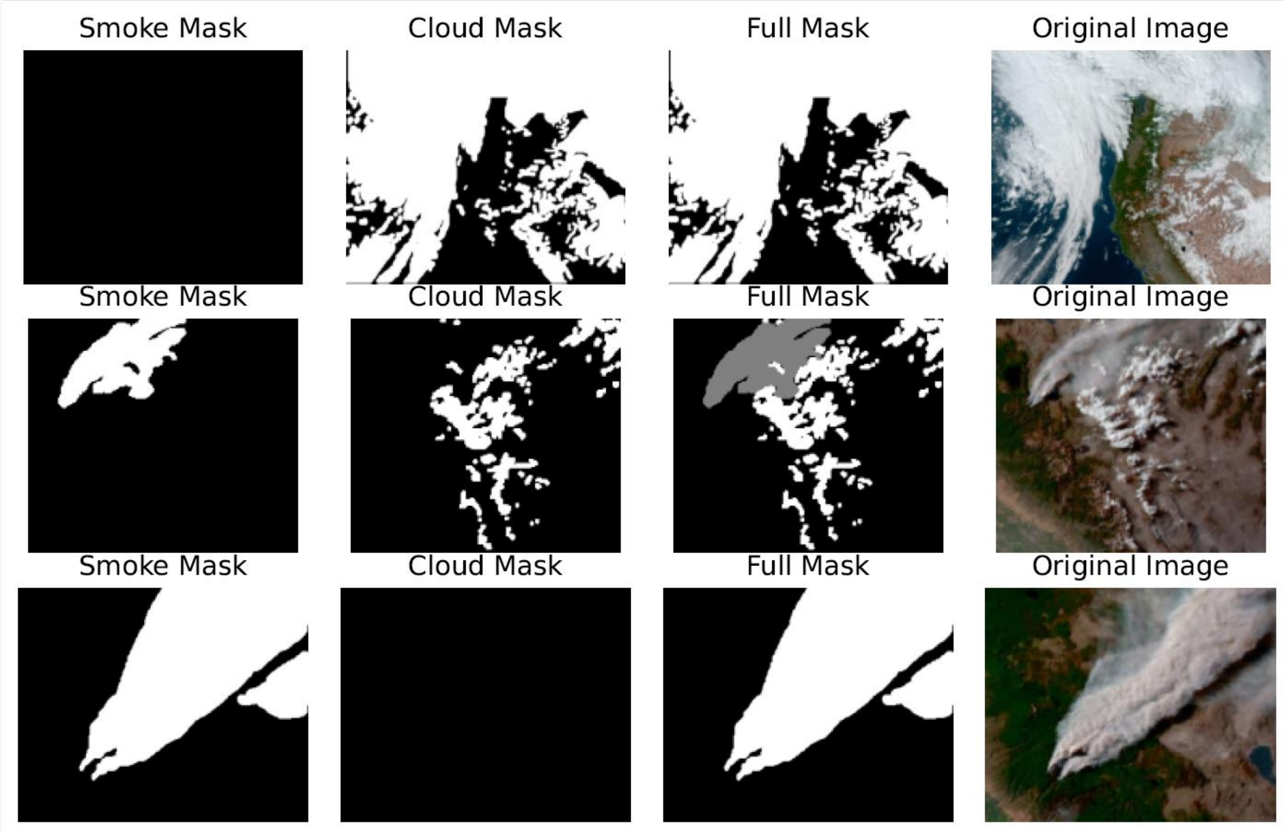
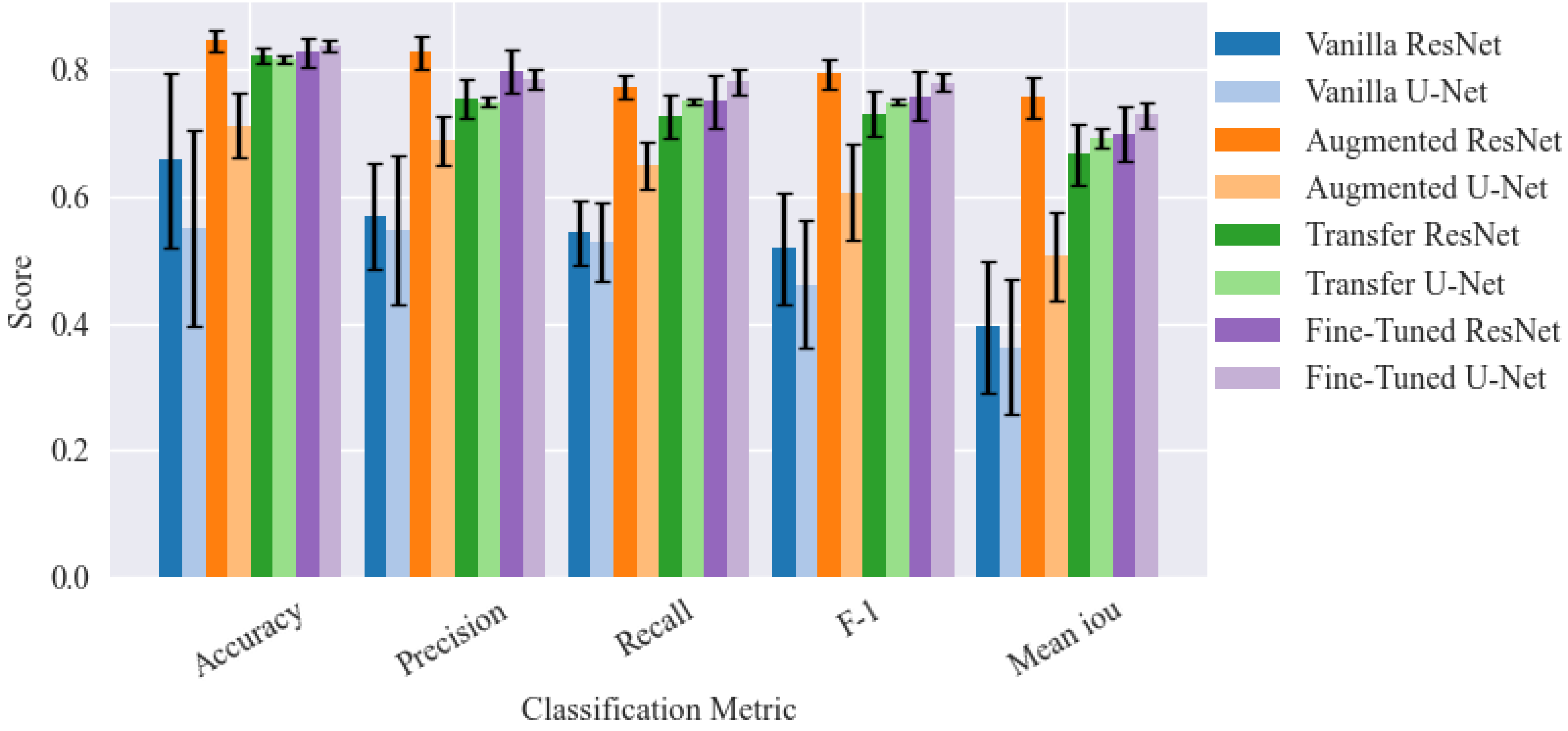



Fig 4: Example training data

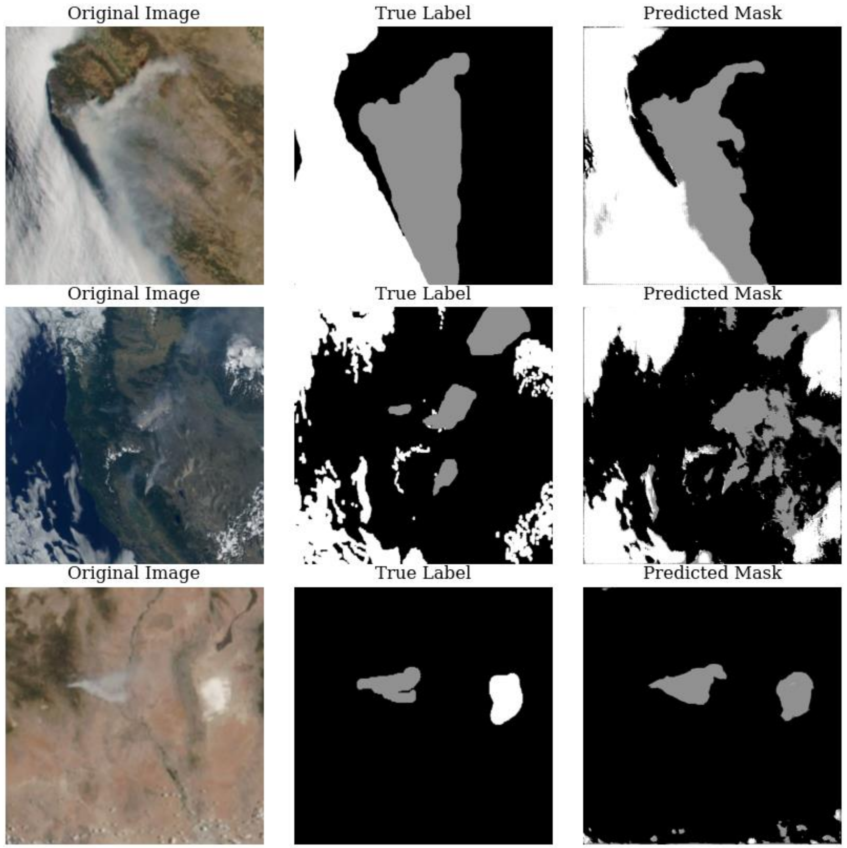
# Smoke and Cloud Segmentation Results

Fig 5: Model performance on 5-fold cross-validation




Gap between U-net and Resnet is **closed** using a pre-trained model backbone, despite Resnet having **16x** more parameters

# Smoke and Cloud Segmentation Results



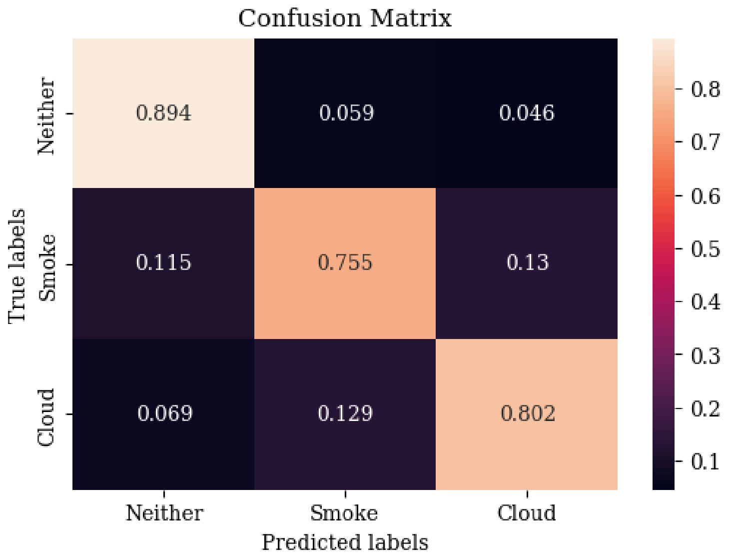




Table 2: Performance of the final model on the test set.

| Class | precision | recall | f1-score | support |
|---|---|---|---|---|
| neither | 0.93 | 0.89 | 0.91 | 3,650,286 |
| smoke | 0.61 | 0.76 | 0.68 | 979,478 |
| cloud | 0.84 | 0.80 | 0.82 | 1,923,836 |
| average (macro) | 0.79 | 0.82 | 0.80 | 6,553,600 |

# Model Demo


GOES-R Satellites
layer: /fire/detection/GOES-R ...
data sets
lock step
follow latest
G16
G17
G18
sat good high med low date
G17 199 21 4 11 08/19 11:02
G17 197 24 0 9 08/19 10:57
G17 200 28 1 10 08/19 10:52
G17 197 24 2 14 08/19 10:47
G17 202 26 3 9 08/19 10:42
hotspots
class sat lat lon
G17 37.4295 -121.6733
G17 37.4287 -121.6983
G17 37.4280 -121.7233
G17 37.4116 -121.4040
G17 37.4109 -121.4290
G17 37.4101 -121.4541
G17 37.4094 -121.4792
high
probable
all
hotspot history
dqf mask bright frp area time
layer parameters ...
Smoke and Cloud Layers
Data Selection
G16
G17
G18
follow latest
clear
show type sat date
smoke G17 08/19 10:54
cloud G17 08/19 10:54
Data Entries
show sat date
G17 08/19 10:54
G17 08/19 10:49
G17 08/19 10:44
G17 08/19 10:39
G17 08/19 10:34
Contour Display ...

# Discussion and Conclusion

- Pre-training improved smaller model performance up to par with larger models
- Self-supervised learning is effective pre-training method for satellite imagery
- Developed a custom pre-trained computer vision model using self-supervised learning + supervised fine-tuning
- The model can improve “cloud contamination” in satellite-based wildfire hotspot detection by distinguishing smoke from clouds using deep learning

# Contact Information

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- Guillaume.p.Brat@nasa.gov
- Joseph.c.Coughlan@nasa.gov

Additional Resources:

- Robust Software Engineering: https://ti.arc.nasa.gov/tech/rse/
- RACE-ODIN: https://nasarace.github.io/race-odin/
- ODIN-rs: https://github.com/ODIN-fire/odin-rs


Thank you!
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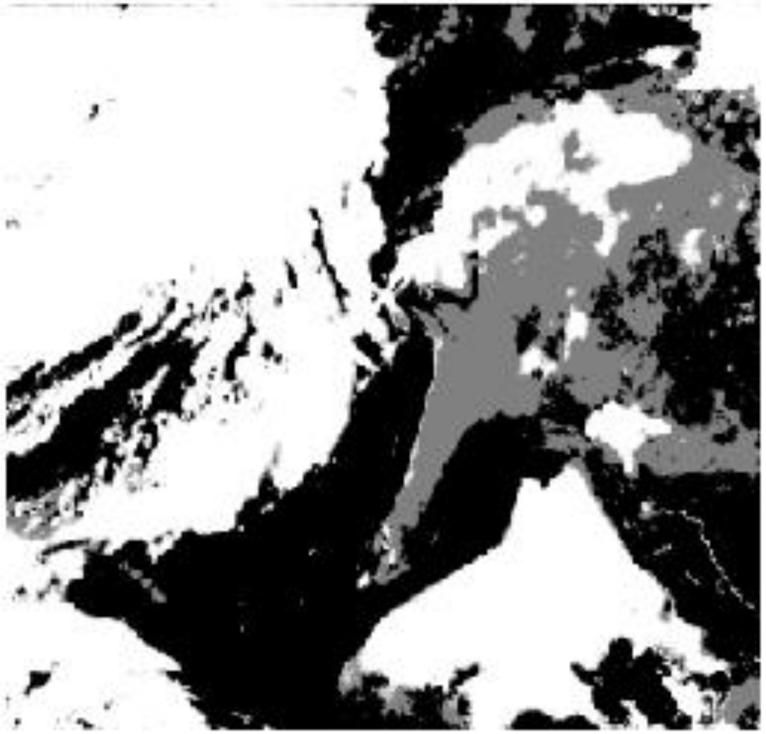
# Backup

# Model Demo: CZU 2020

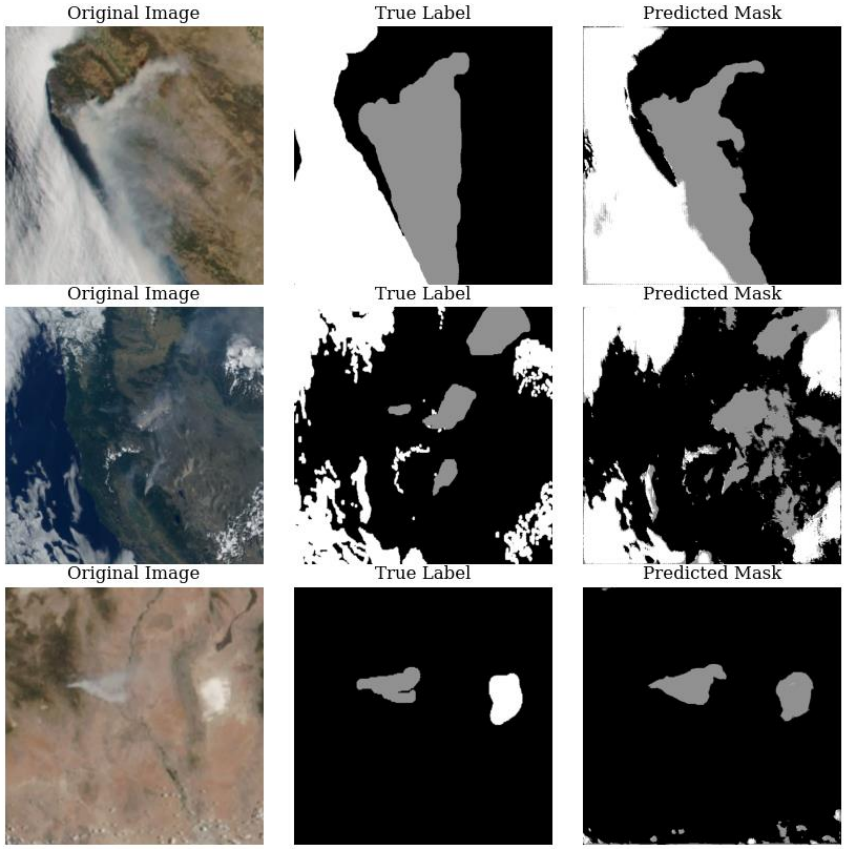
Input Image

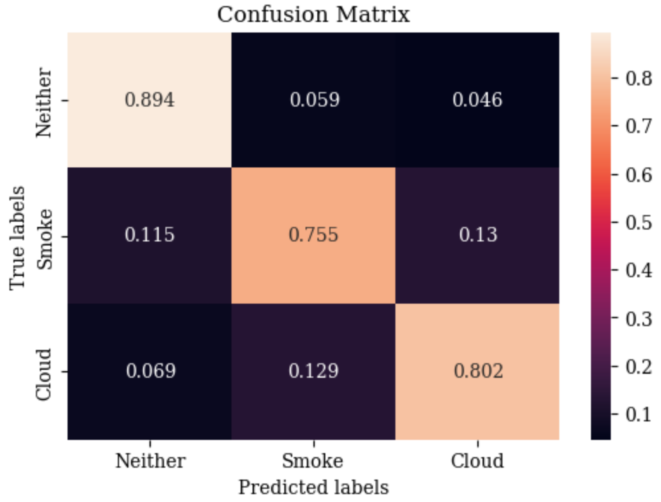
Predicted Mask



# Model Demo: CZU 2020

# Smoke and Cloud Segmentation Results

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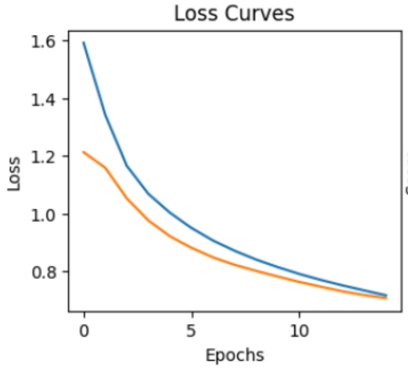


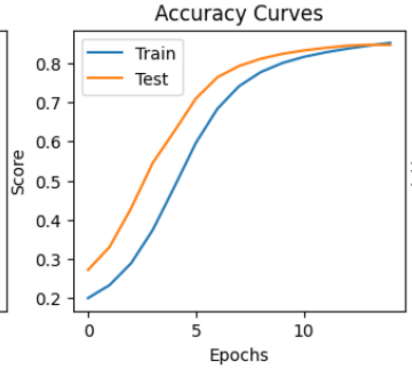


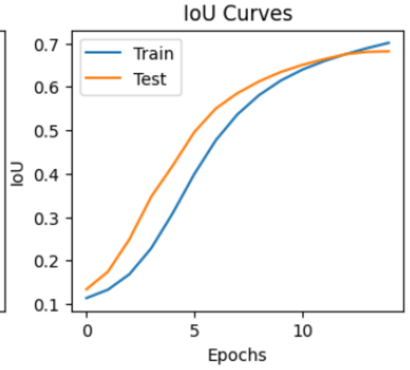

# Model Implementation

- Open Data Integration (ODIN) for wildfire response – actor- based framework for building custom microservices and web applications

| Source | Execution Time (sec) |
|---|---|
| Image Import | 0.132 ± 0.009 |
| Segmentation | 52.342 ± 3.373 |
| Post-Processing | 21.813 ± 6.175 |
| Total | 74.288 ± 7.576 |