Deep Learning Approaches for Cloud Property Retrieval: Comparing Fine-tuning with Domain-Specific Architectures

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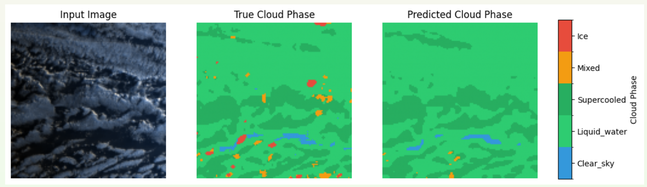
Deep Learning on ABI Data

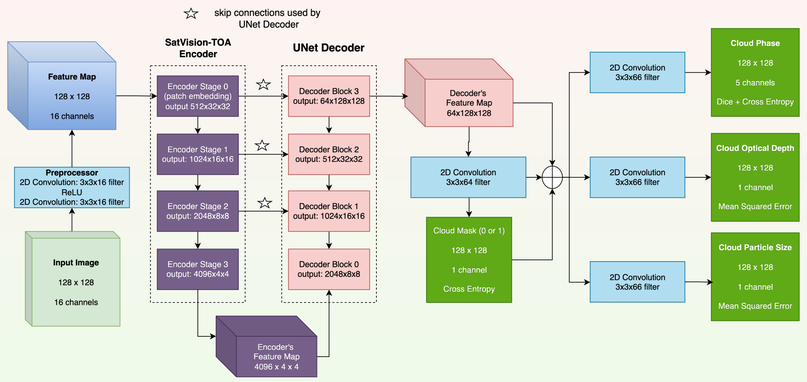
- Satellites are the primary source of global cloud data
- SatVision-TOA is a transformer-based foundation model trained on 14 MODIS spectral bands
- Transitioning to Advanced Baseline Imager (ABI) which detects 16 spectral bands



Cloud phase prediction from ABI image

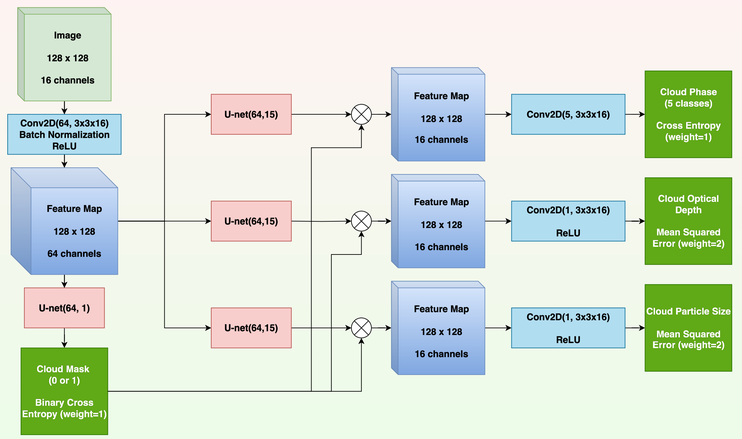
- Developed and compared deep learning techniques to retrieve four level-2 cloud properties from ABI data.
  - Finetune SatVision-TOA on ABI dataset
  - Train deep learning models from scratch

Finetuned Multi-task Design



- UNet Decoder: Input is downsampled as it goes through encoder stages and upsampled as it goes through the decoder stages
- Skip connections recover spatial detail lost during downsampling
- Cloud Mask prediction appended to the input of other task heads
- loss $= 2 \cdot$ mask loss $+ 1 \cdot$ phase loss $+ \frac{1}{100}(MSE_{COD} + MSE_{CPS})$

Multi-task From Scratch Design



- Shared encoding convolution extracts common spatial features
- Individual U-nets to capture high and low level features
- Cloud Mask prediction appended to U-net feature maps
- Total loss is weighted for each task

Cloud Properties

Cloud property retrieval is vital for understanding Earth's climate, energy balance, and hydrological cycle.

- **Cloud Mask:** Cloudy or not cloudy
- **Cloud Phase:** Clear, Liquid, Supercooled, Mixed, Ice
- **Cloud Optical Depth (COD):** Measure of cloud opacity (higher = more opaque)
- **Cloud Particle Size (CPS):** Measure of average cloud particle radius

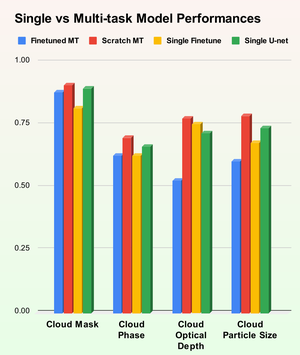
Cloud mask and phase properties → segmentation tasks
COD and CPS properties → regression tasks

Practical Applications

- Accurate retrieval algorithms for cloud properties reduce need for manual labeling of data
- Parameter efficient fine-tuning methods reduced time to train with FM
- Support future weather and climate research

Finetuning vs From-Scratch Results

Model	Task	mIOU	Task	r^2
Multitask Models				
Fine Tuned MT	Mask	**0.881**	COD	0.527
	Phase	0.627	CPS	0.605
From Scratch MT	Mask	**0.909**	COD	**0.775**
	Phase	**0.700**	CPS	**0.786**
Individual Models				
Fine Tuned	Mask	0.816	COD	**0.754**
	Phase	0.627	CPS	**0.680**
From Scratch	Mask	0.896	COD	0.717
	Phase	0.664	CPS	0.738



Conclusions

- Multi-task setup from scratch improved predictions across all target variables
- Finetuning SatVision-TOA shows promise with regression modeling as an area for improvement
- Parameter-efficient fine-tuning methods may be leveraged in order to reduce computational overhead and improve model performance

References

[1] D. Murphy, K. Zhang, C. Parten, A. Sterling, H. Zhang, et al., tech. rep. HPCF–2025–4, 2025.

[2] D. Murphy, K. Zhang, C. Parten, A. Sterling, H. Zhang, et al., REU Symposium, *ICDM 2025*, 2025.

HPCF

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