

LEVERAGING SPATIAL CONTEXT DATA TO IMPROVE HOLODEC SEGMENTATION MODEL PERFORMANCE

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SIPARCS 2023 & NCAR MILES - Boulder, CO*

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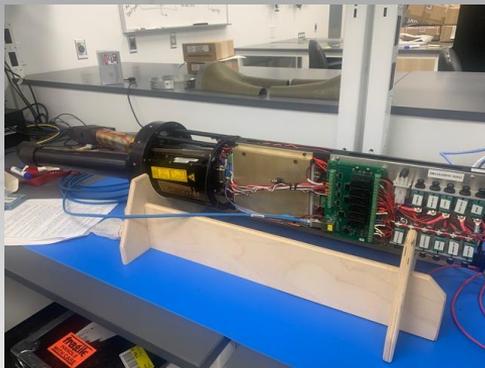


MOTIVATION

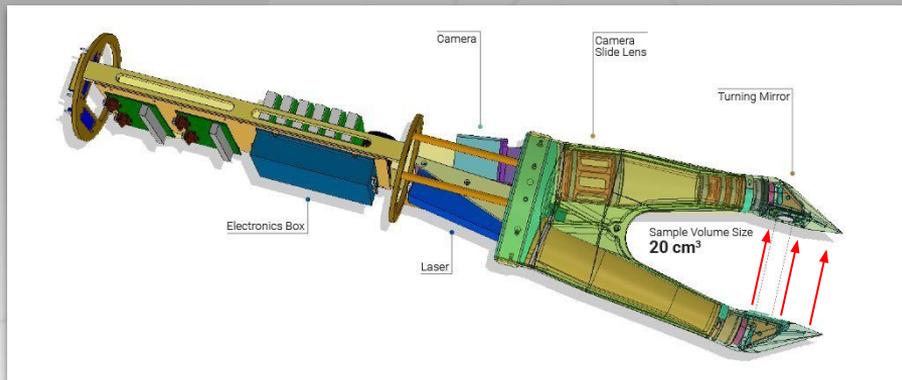
- HOLODEC-ii hydrometeor sensor from NCAR EOL¹
- Samples 20 cubic centimeter atmosphere sample
- Returns inline complex hologram, use fourier transform to reconstruct three-dimensional image



Mounted HOLODEC Sensor



HOLODEC Hardware



EOL HOLODEC Schematic

MOTIVATION

- Raw sensor data to hydrometeor attributes
- Requires holograms be reconstructed at target depth
- Wave propagation algorithm to unpack sensor depth dimension²



HOLOSUITE METHOD

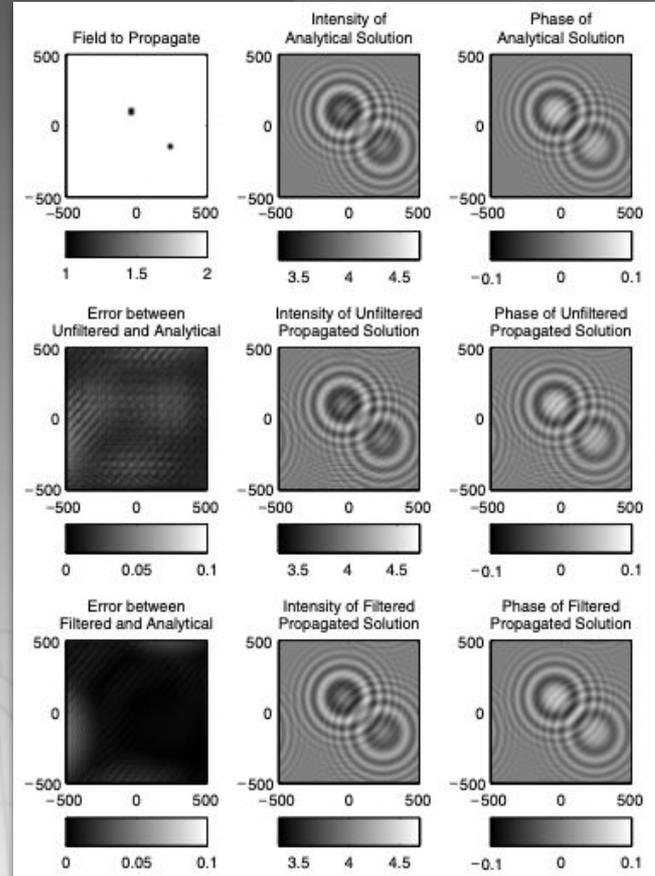
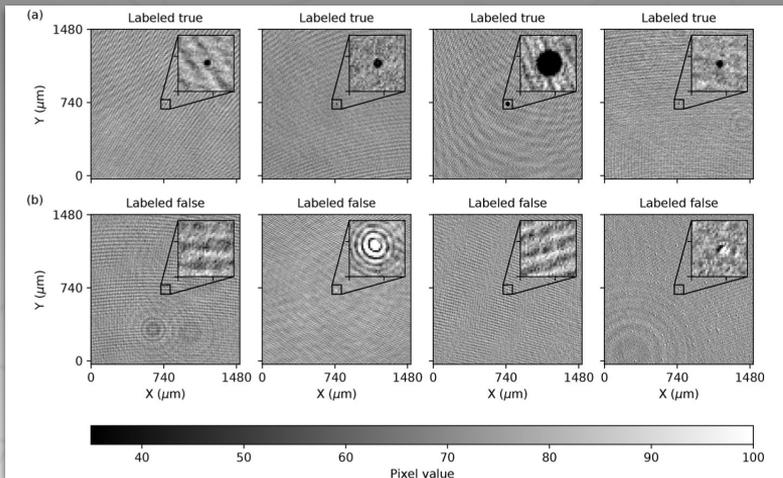
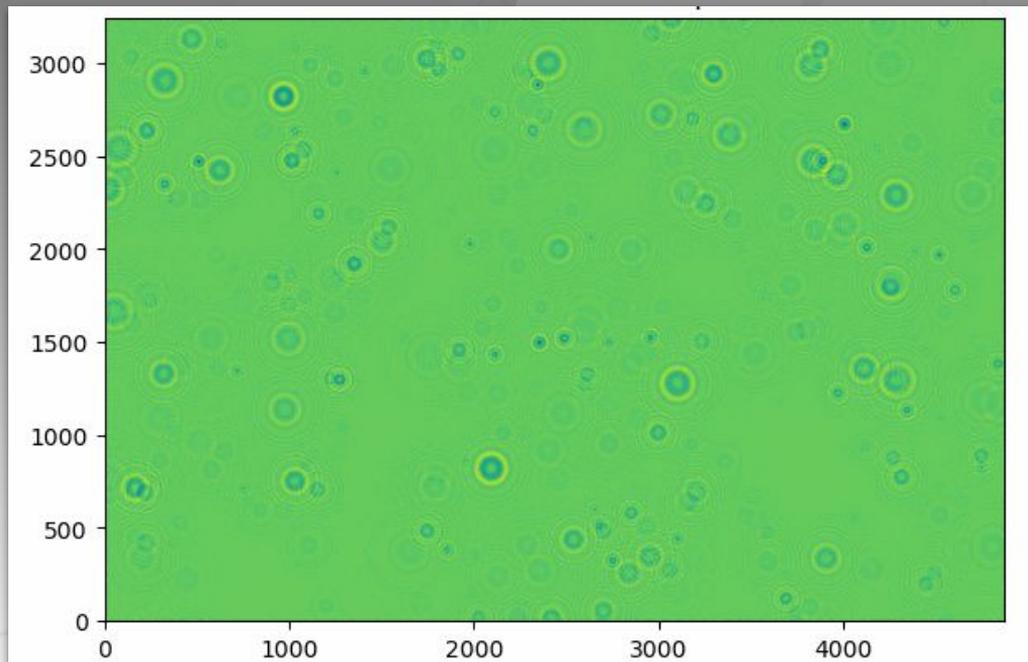


IMAGE REFOCUSING

- Sensor data is noisy and particles are sparse
- Water particles only for geometric simplicity
- Synthetic data here onwards



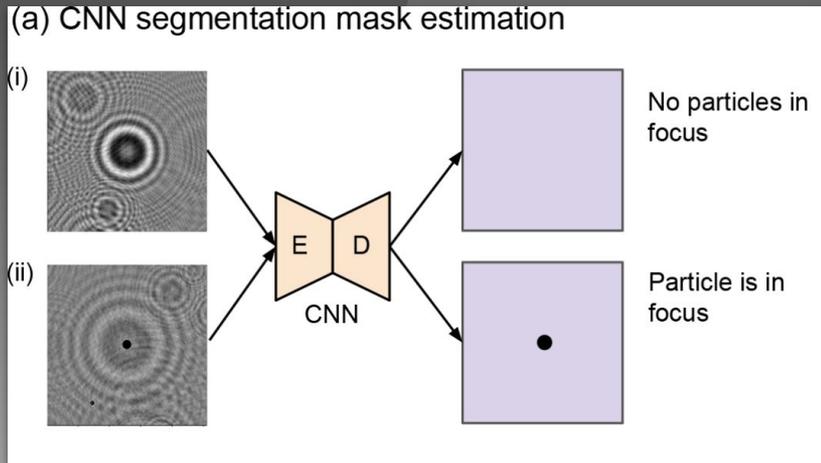
Sample Particle Prediction Labels



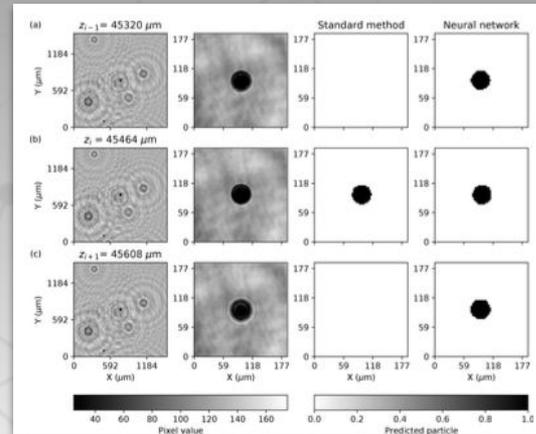
Sample Synthetic HOLODEC Hologram Data

HOLODEC-ML

- 3D complex tensor \rightarrow 2D propagation image
- NCAR MILES: ML Powered particle segmentation algorithm³
- PyTorch SMP network trained on synthetic particle data
- Images treated as independent, classical segmentation problem
- Higher false positive rate in sensor depth direction, particle spans reconstruction depths



Segmentation Model Outline

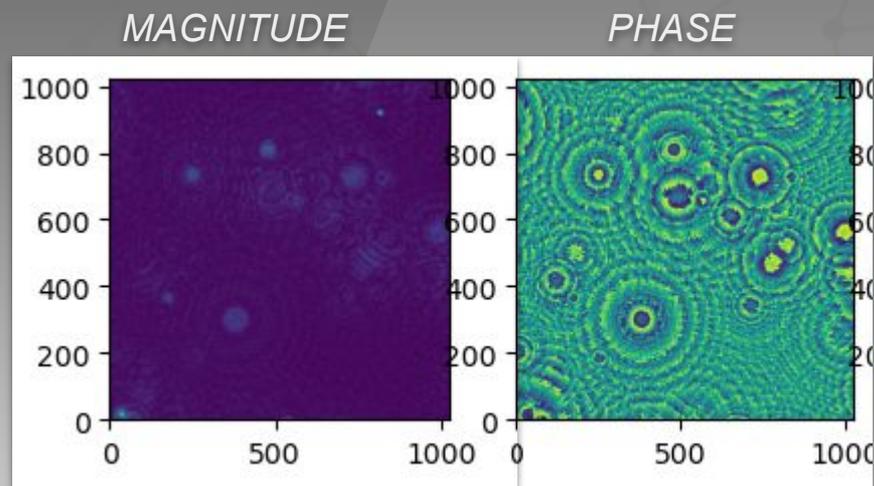


Sample Network Input Across Adjacent Depths



1. HOLOGRAM PHASE DATA

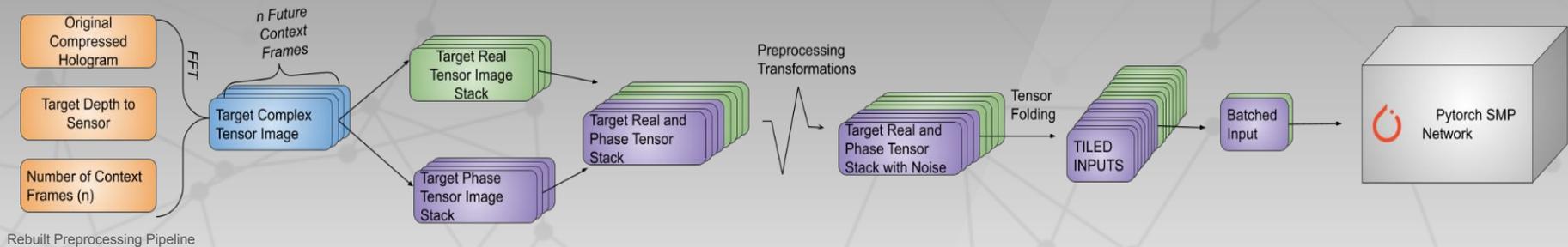
- Sensor data is complex wave representation ($a+bi$)
- Include magnitude and phase
- Old method: absolute value to convert into SMP compatible image
- New method: give magnitude and phase tensors to model, capture Z depth detail better
- Wave phase more variable with respect to propagation distance



Sample Network Input

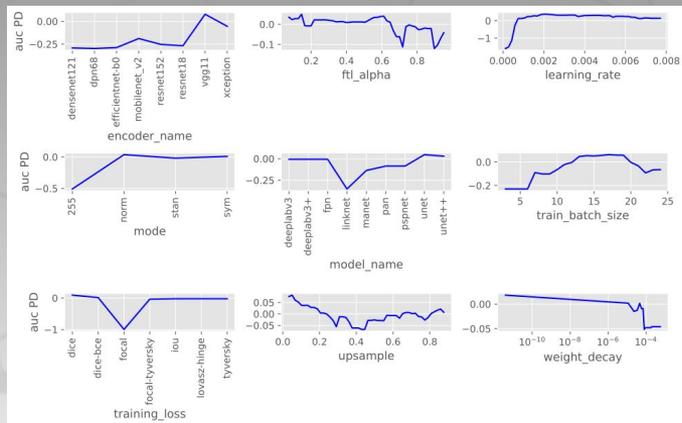
1. SENSOR DEPTH CONTEXT DATA

- Don't treat propagation distance frames as independent
- Give model propagation context in positive sensor direction
- Stacked in tensor color channel along with phase/magnitude components

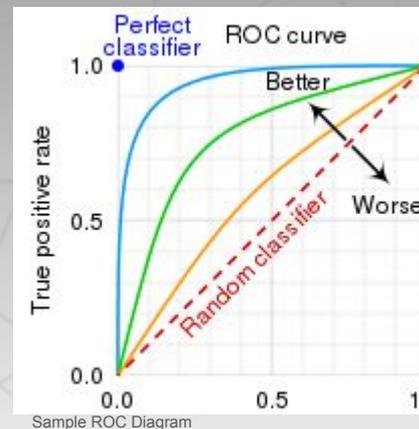


2. FULL-HOLOGRAM INFERENCE

- Goal: HOLODEC hologram -> particle prediction mask data
- New metric - area under receiver operating characteristic curve (0.5 is worst, 1.0 is best)
- Evaluated on small fixed sample, realistic inference simulation
- Greatly improved optimization time w.r.t. Minimizing FPR

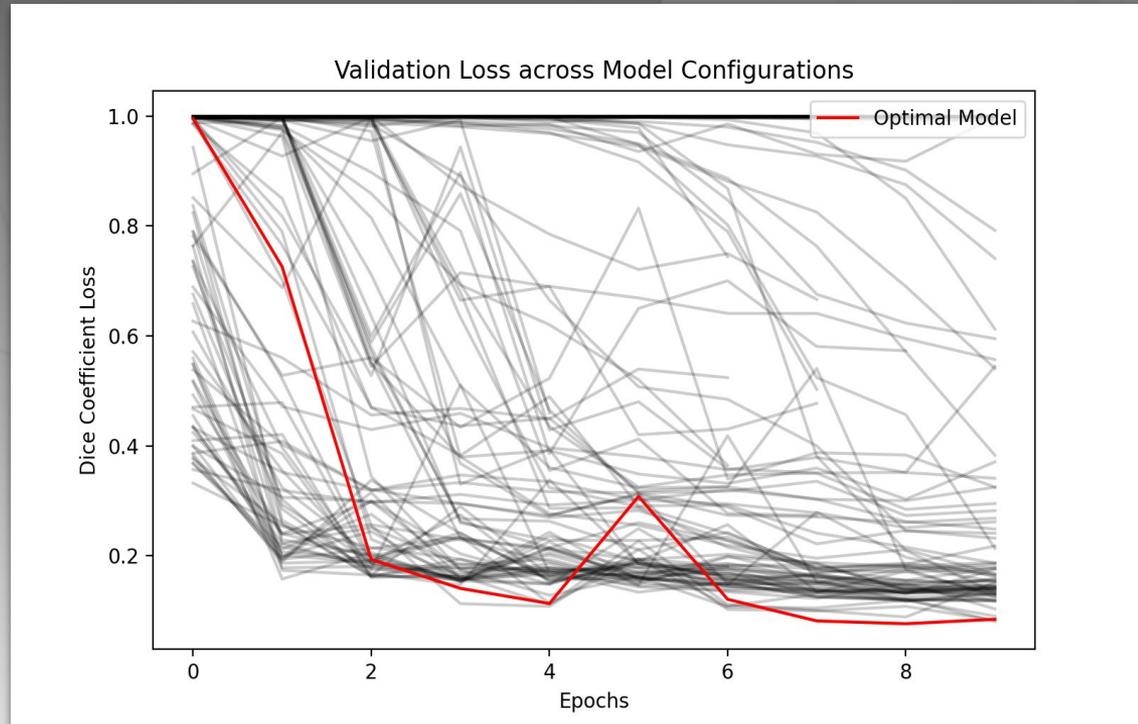


Feature Importances w.r.t AUROC Objective



HYPERPARAMETER OPTIMIZATION

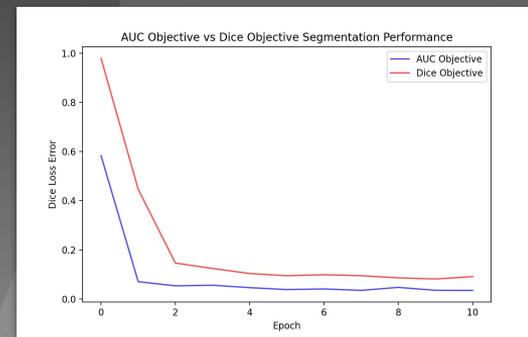
- Tuned on ECHO,
NCAR MILES
optimizer
 - Extension of Optuna
- Optimal configuration
of hundreds of trial
configurations
- Powered by CISL
Casper



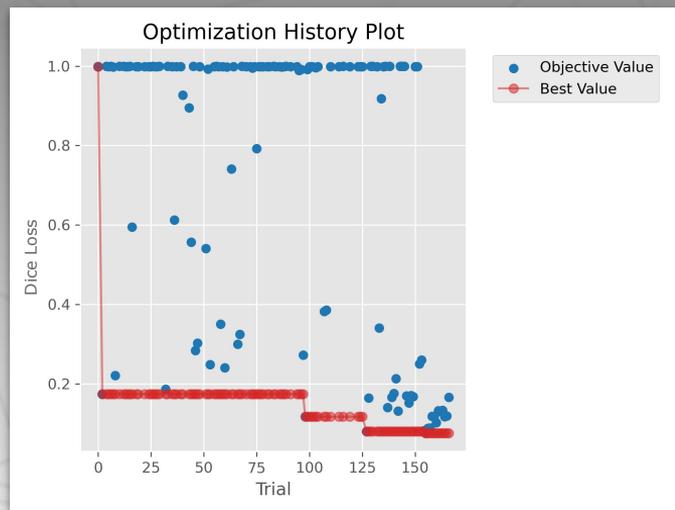
ECHO Model Configuration Performance across Time

PERFORMANCE

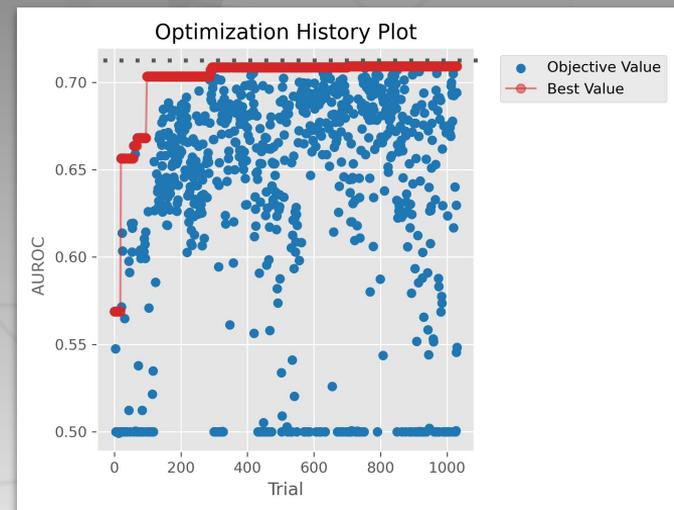
- Best validation dice loss with added context: 0.073
- Best AUC maximizing AUROC: ~ 0.7 , dice loss of ~ 0.03
- Greatly improved optimization speeds



HOLODECML Performance with Dice and AUC Objective Functions



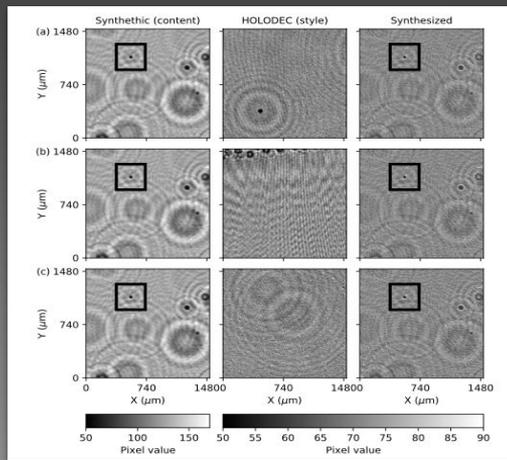
ECHO Dice Coefficient Loss and Best Value Across Time



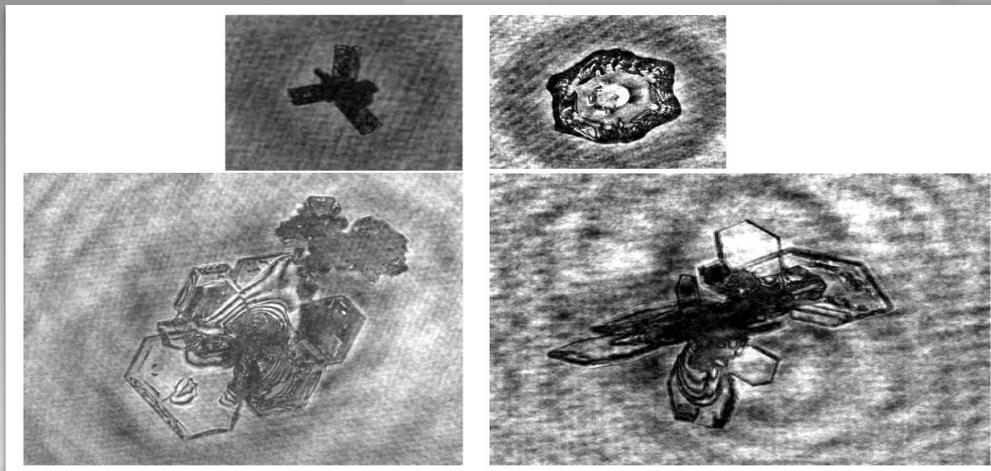
ECHO Area Under ROC and Best Value Across Time

FUTURE WORK

- GAN-stylized synthetic data to mirror real data⁴
- Ice particulate segmentation
- Goal: on-the-fly image inference
- Evaluate performance on different sensors, datasets, campaigns



GAN-Stylization of Synthetic Data



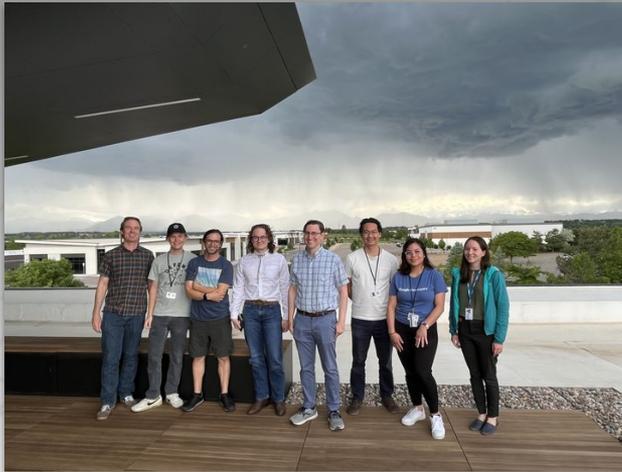
Ice particle segmentation

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experience!



NCAR Miles Team at Vaisala in Louisville



McLovin the Australian Shepherd wearing a CISL hat



SIPARCS Interns

REFERENCES

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- ³Schreck, J. S., Gantos, G., Hayman, M., Bansemer, A., & Gagne, D. J. (2022). Neural network processing of holographic images. *Atmospheric Measurement Techniques*, 15(19), 5793-5819.
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