LEVERAGING WAVE AND SPATIAL CONTEXT DATA TO IMPROVE HOLODEC SEGMENTATION MODEL PERFORMANCE

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OVERVIEW

This project expanded upon the HOLODECML hydrometeor segmentation model for HOLODEC-ii particle holograms by incorporating holographic phase data, sensor depth context data, refined evaluation methods, and streamlined training and execution to improve water particle detection accuracy and efficiency.

Figure 1 - HOLODEC-ii Hydrometeor Detector

IMPROVEMENTS

CHANGES TO PREPROCESSING
- More efficient tensor tiling and reconstruction scheme
- Rebuilt PyTorch dataloader to include context information
- Upsampled training data
- Variable loss function weights

CONTEXT ADDED TO MODEL
- n "lookahead" context frames ahead of target depth to sensor
- Phase component of complex tensor from original data
- Larger image tiles, more efficient GPU memory usage

FULL FRAME INFERENCE
- Collect performance metrics from model on entire sensor images, evaluate using AUROC
- Simulate realistic use performance

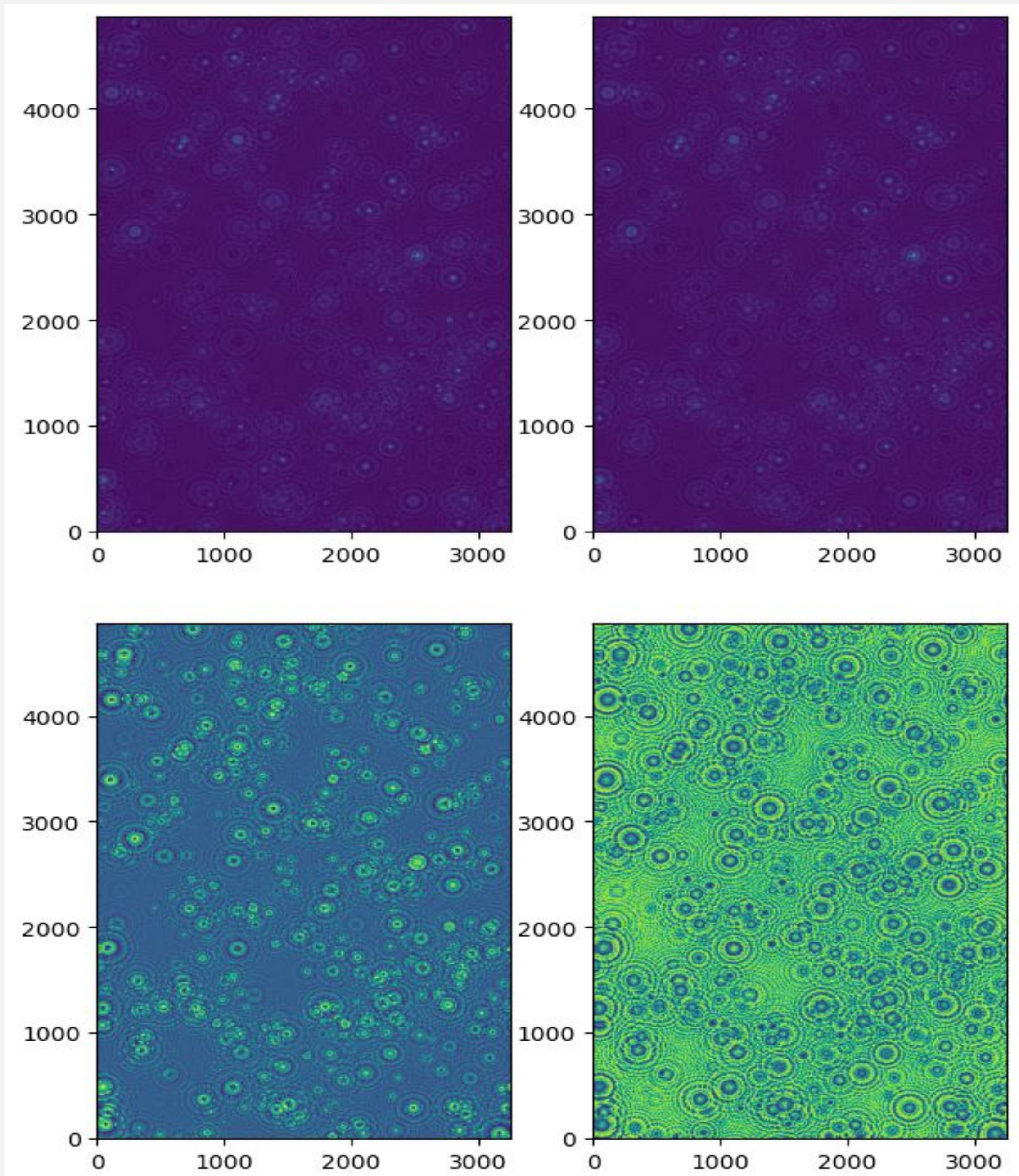

Figure 2 - HOLODEC Synthetic Example Data w/ Lookahead

OPTIMIZATION

HYPERPARAMETERS
- Optimized using ECHO-OPT, extension of Optuna hyperparameter framework
- Custom built at NCAR MILES for earth science models

TUNING
- Performed on CISL Cheyenne computing beds
- Optimal configuration over >600 parameter settings

FUTURE WORK

- Expand from water (sphere) to ice (polygon) particle detection
- Optimize runtime, goal is on-the-fly particle recognition
- GAN-stylized training data to accurately simulate campaign data
- Create models for data from different lasers and sensor architecture

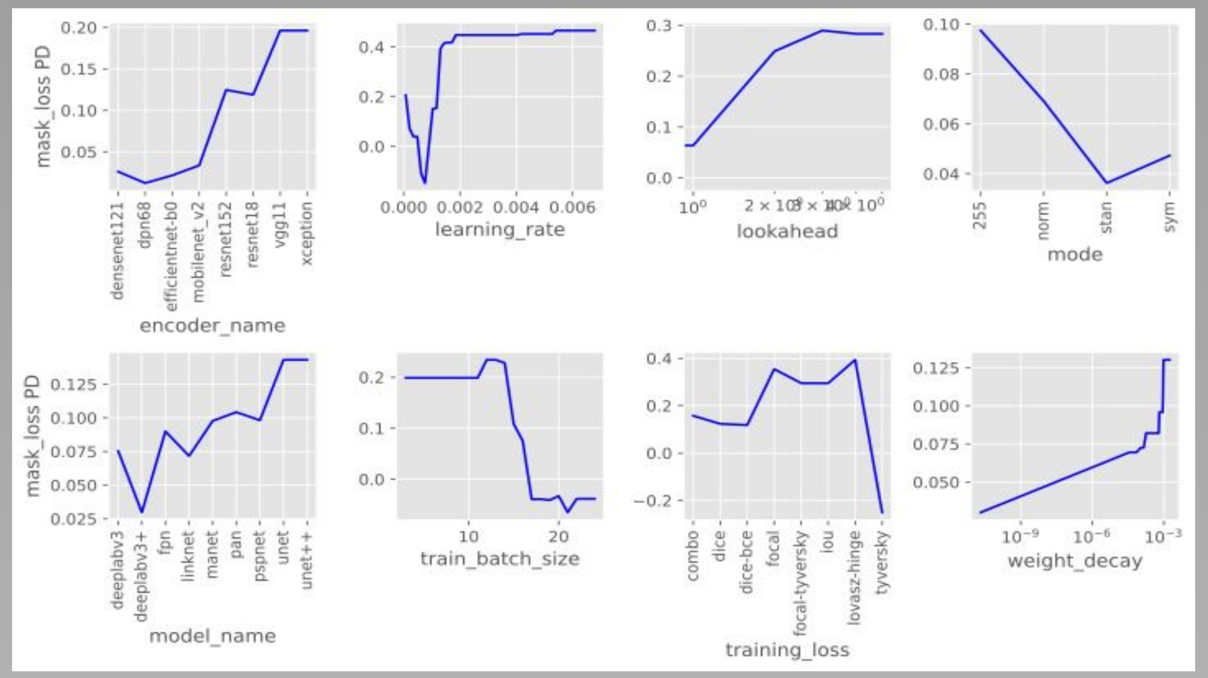

Figure 3 - Partial Loss Dependence of Preprocessing Hyperparameters (n = 353)

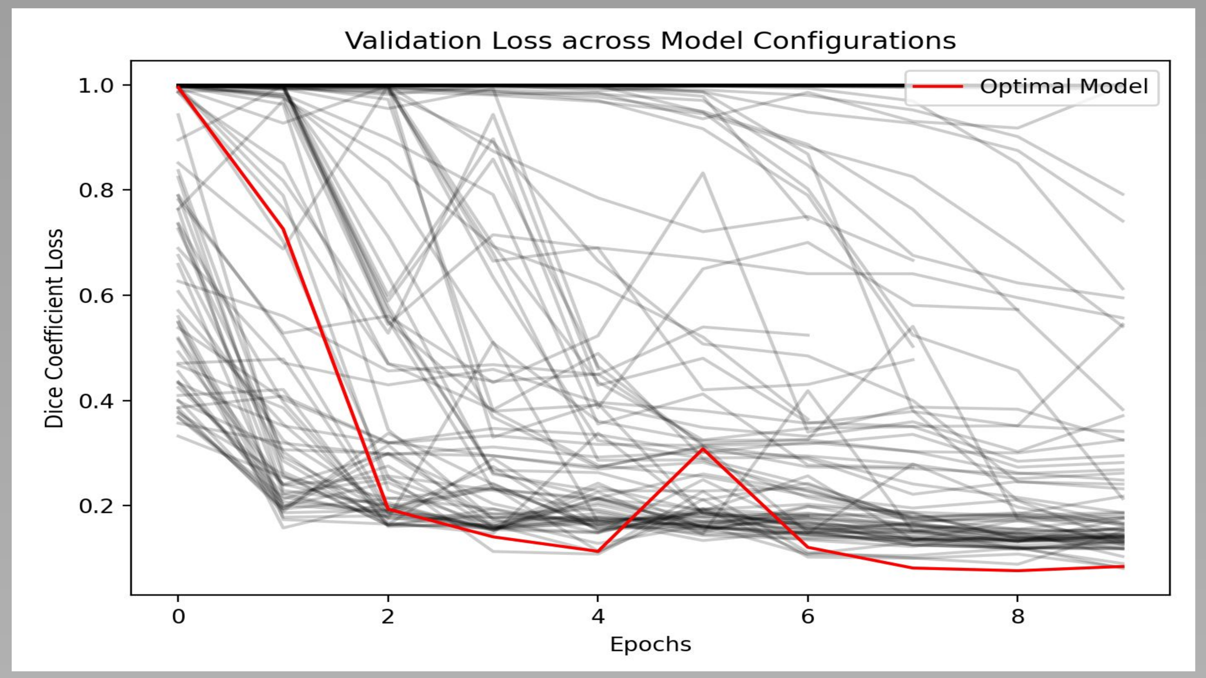

Figure 4 - ECHO Model Dice Loss Variations with Preprocessing Transformations (n = 353)

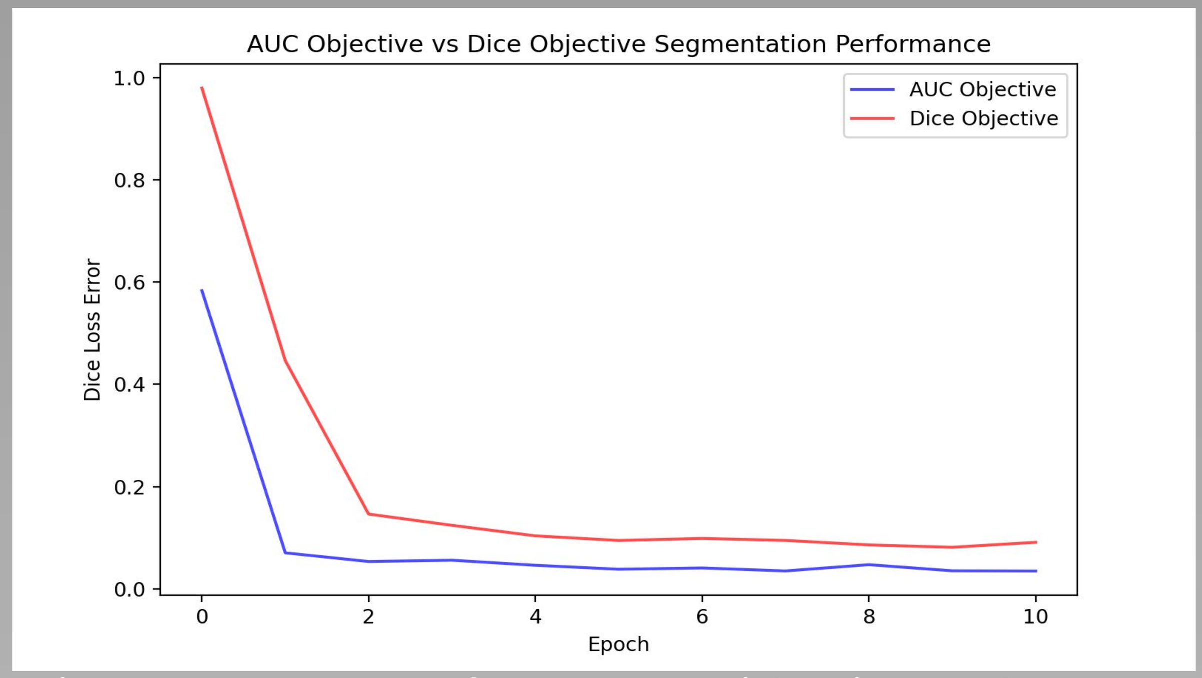

Figure 5 - Loss Performance With Dice and AUC Objectives (Dice Coefficient)

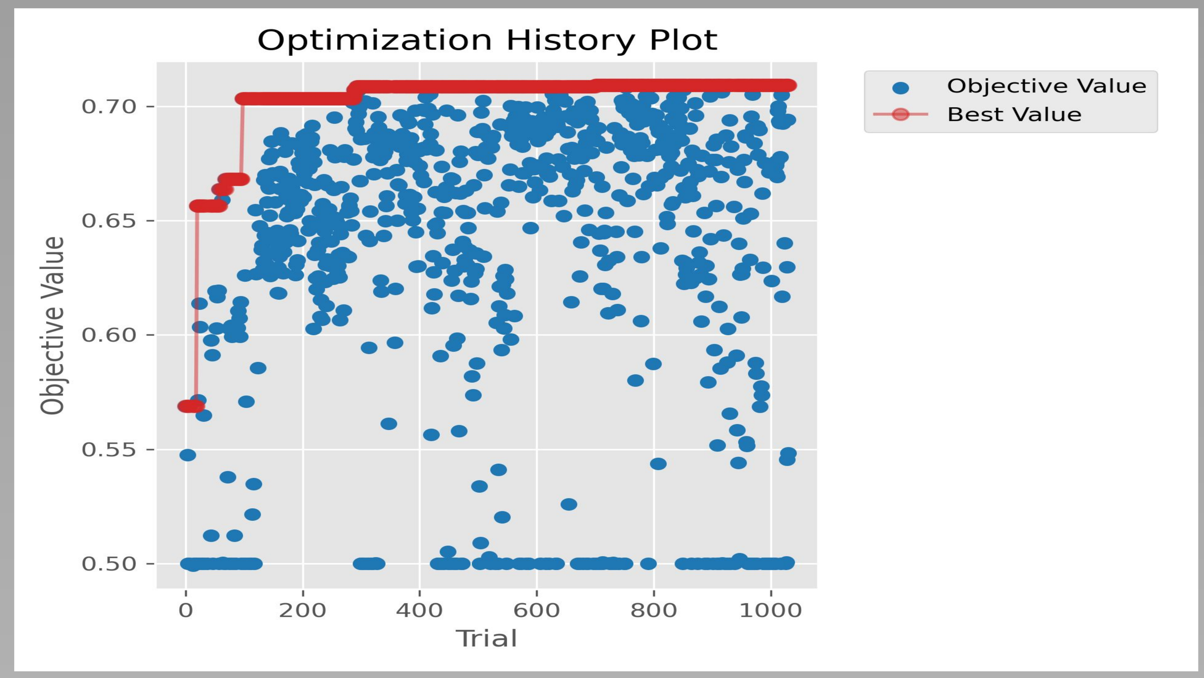

Figure 6 - AUROC Across ECHO Trials (n = 1031)

PERFORMANCE

- Loss metrics: Dice loss for train, AUROC on full images for evaluation
  - Dice Loss =1 - [2TP / (2TP + FP + FN)]
- Best performance with preprocessing: 0.073 Dice loss *(fig 4)*
- Best performance with realistic evaluation: 0.035 Dice loss *(fig 5)*
- Holdout hologram validation method better reflects practical use-case performance for campaigns
- AUROC converges to ~0.7 regardless of hyperparameters
- Inherent limit to model class within problem space? Could resolve with more computing power (larger batch size)
- New validation metric yields better model within ten epochs *(fig 5)*
- Higher accuracy model within fewer epochs requires less resources to train and develop

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