Creating a Convolutional Neural Network to Monitor New York State Mesonet Daytime Precipitation from Camera Images

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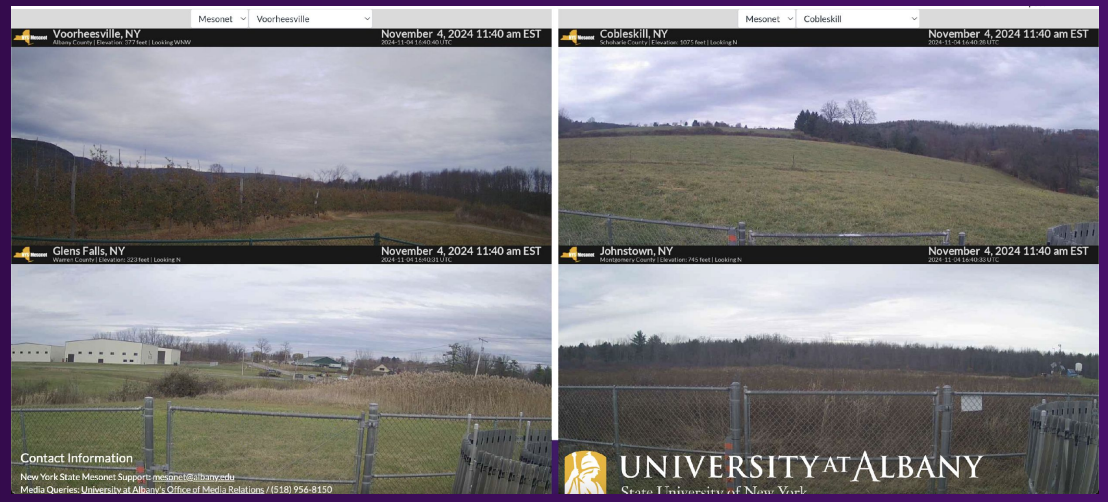
Motivation

- The NYSM cameras monitor static sites, which can be viewed on the NYSM site
- This is an intensive process which requires many work-hours and concentration
- This sentiment was shared by the NWS Albany
- Attempt to detect precipitation at the time it occurs



Problem

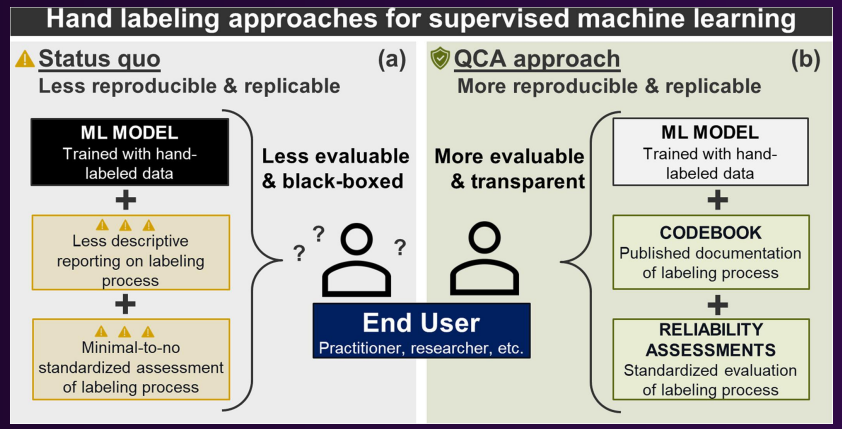
- How do we monitor the conditions more efficiently than just staring at a screen?
- Can we identify the onset/cessation of precipitation?
- Can we use this information to supplement sparsely observed areas?

Methodology

- Using Machine Learning (Convolutional Neural Network classifier), create an ML model that can classify images into the following categories:
  - Rain, Snow, Clear, Obstructed
- Want to make this ML model generalizable

Methodology (Cont.)

- In pre-processing, introduce trustworthiness in the dataset by using a technique called Inter-Coder reliability trials (Wirz et al., 2024).
  - This uses the quantitative content analysis (QCA) framework to label images across multiple labelers and sites.
  - When doing QCA, we create a codebook which allows any current or future labelers to follow a structured guide.



Wirz et al., 2024 (Fig 1)

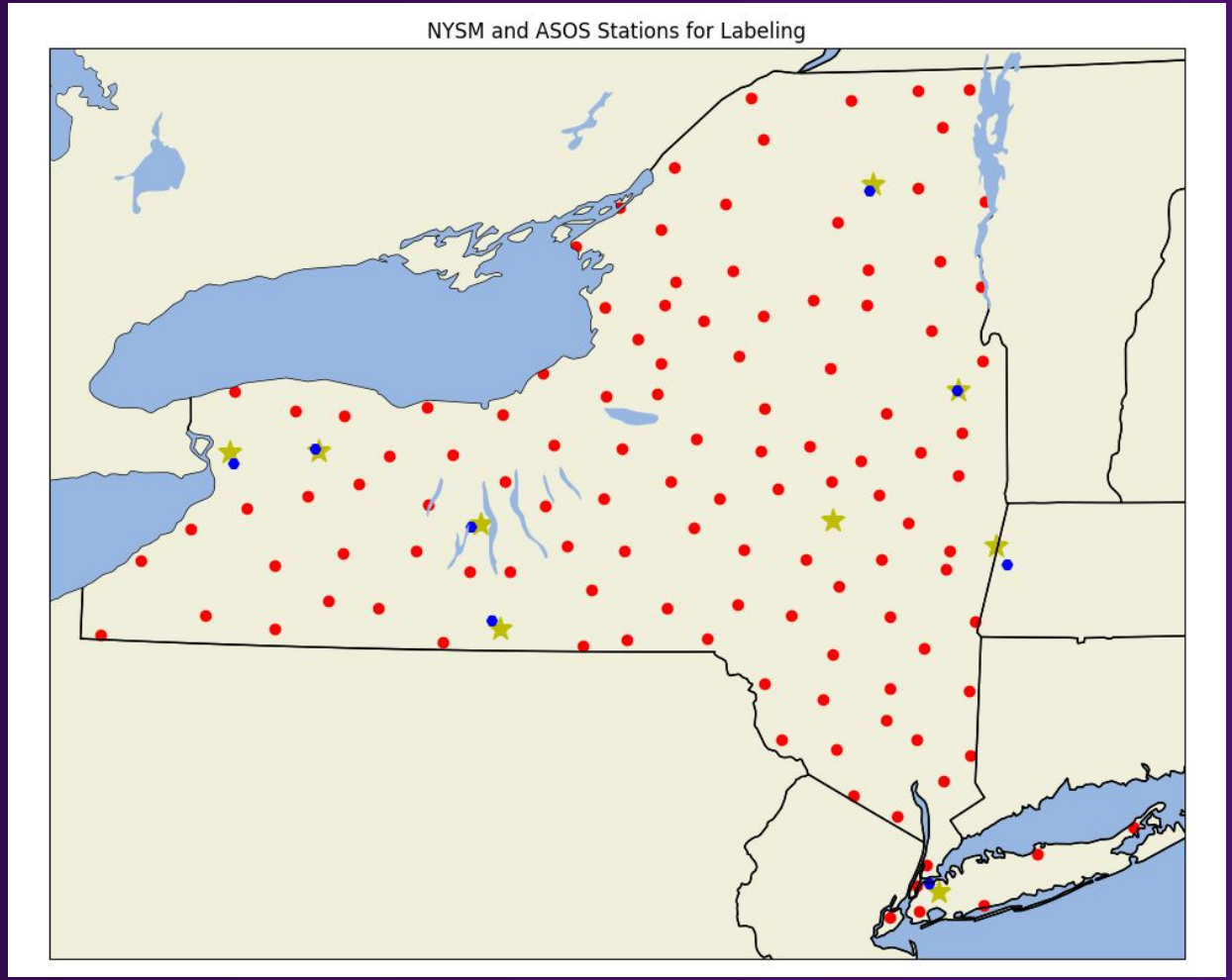
Final Intercoder Reliability trial

- Used 5 people to independently label a dataset of 30 images across the 4 classes
- Reach a Krippendorff's alpha of 0.926 (Krippendorff, 2007)

Number of Labelers	5
Number of Cases	30
Number of Decisions	150
Krippendorff's Alpha	0.926

Datasets

Station	Number of Images in Dataset
Glens Falls (GFAL)	2039
Elmira (ELMI)	2239
Stephentown (STEP)	3105
Buffalo (BUFF) - Future	1310
Cobleskill (COBL) - Future	1890
Queens (QUEE) – Future	0
Batavia (BATA) - Future	0
Gabriels (GABR) - Future	0
Penn Yan (PENN) - Future	0



Preparing the datasets

- **Single Site Model**

Training Data – GFAL – 80% of Data	Validation Data – GFAL – 20%

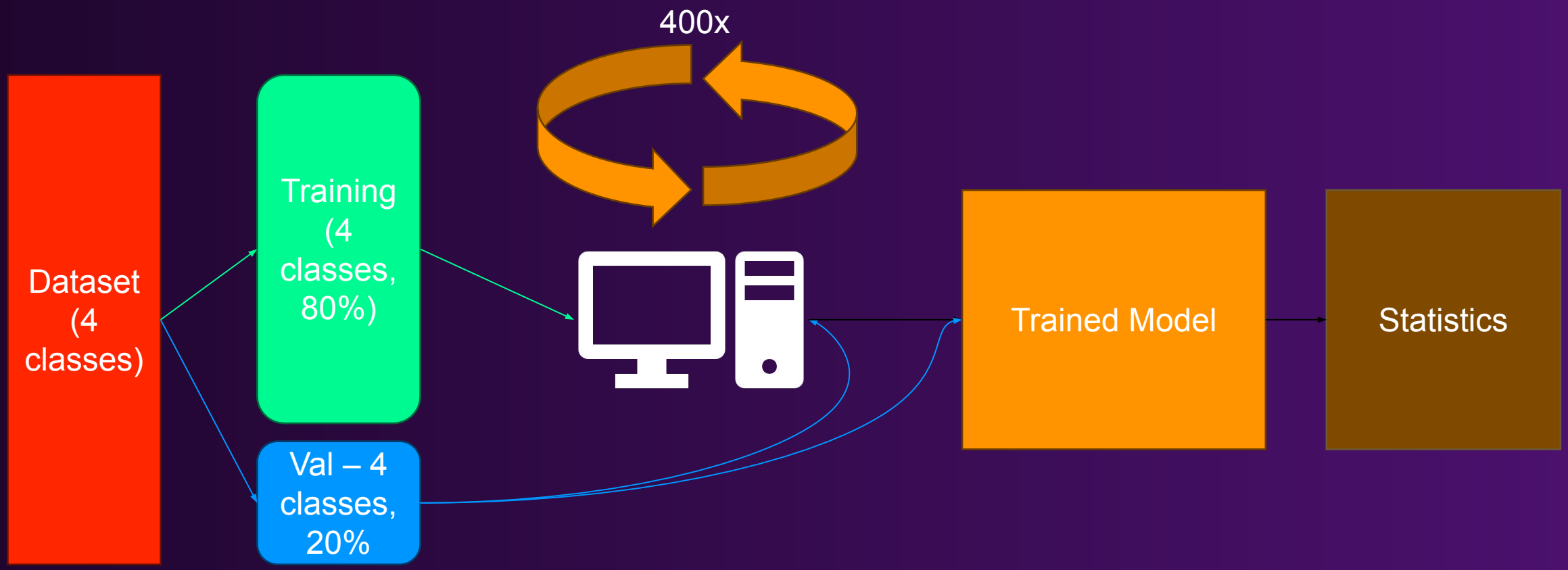
- **Site-Specific Split**

Training Data – GFAL – 100% of GFAL Data	Validation Data - ELMI – 100% of ELMI data

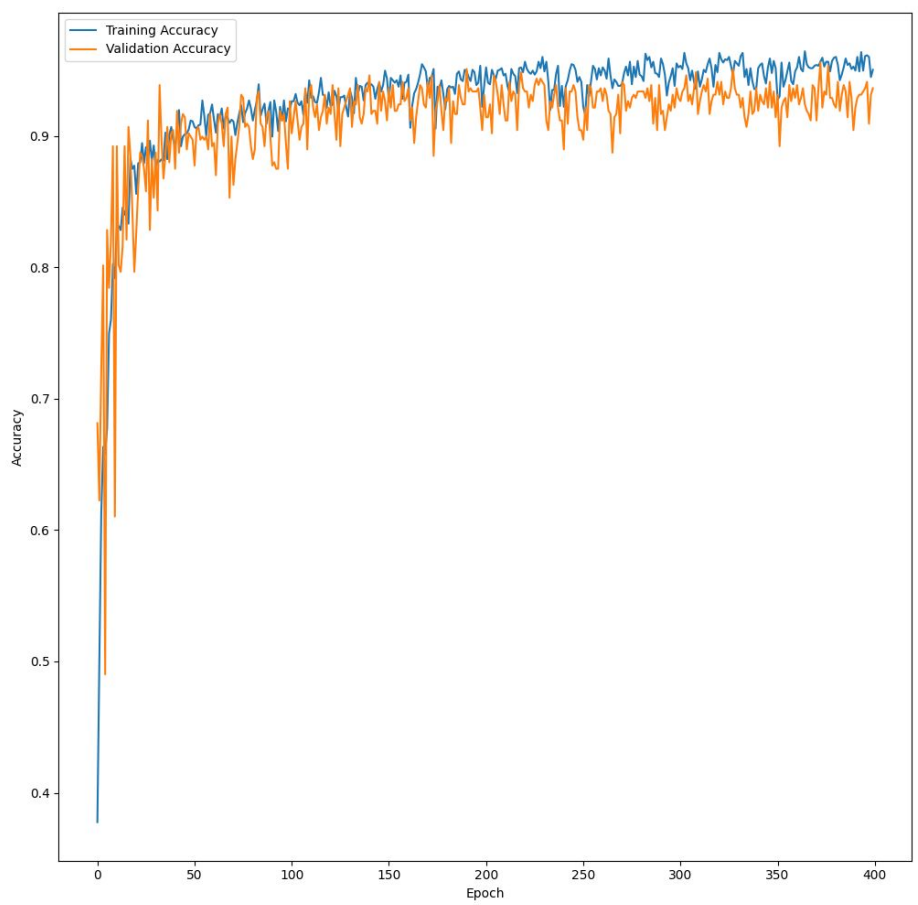
- **Combined Datasets**

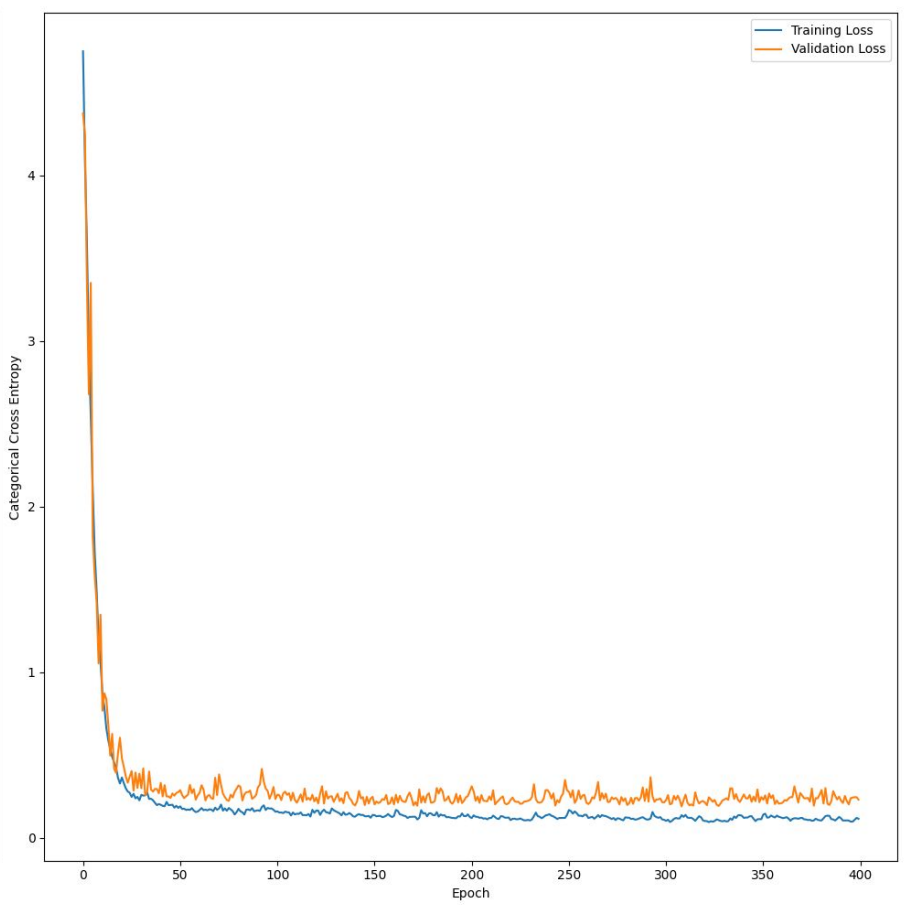
Training Data – GFAL and ELMI – 80% of Data	Validation Data – GFAL and ELMI – 20% of Data

Machine Learning Workflow



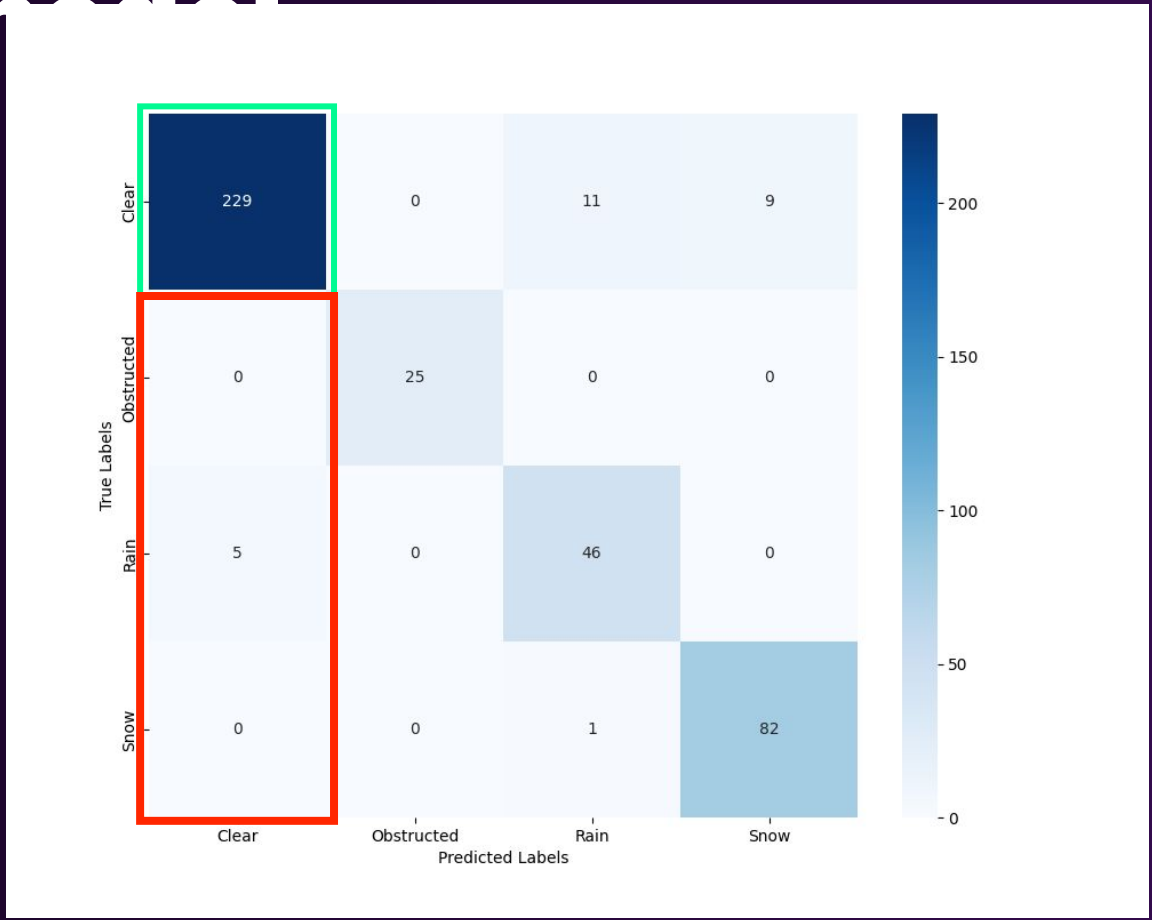
Machine Learning – Single Site

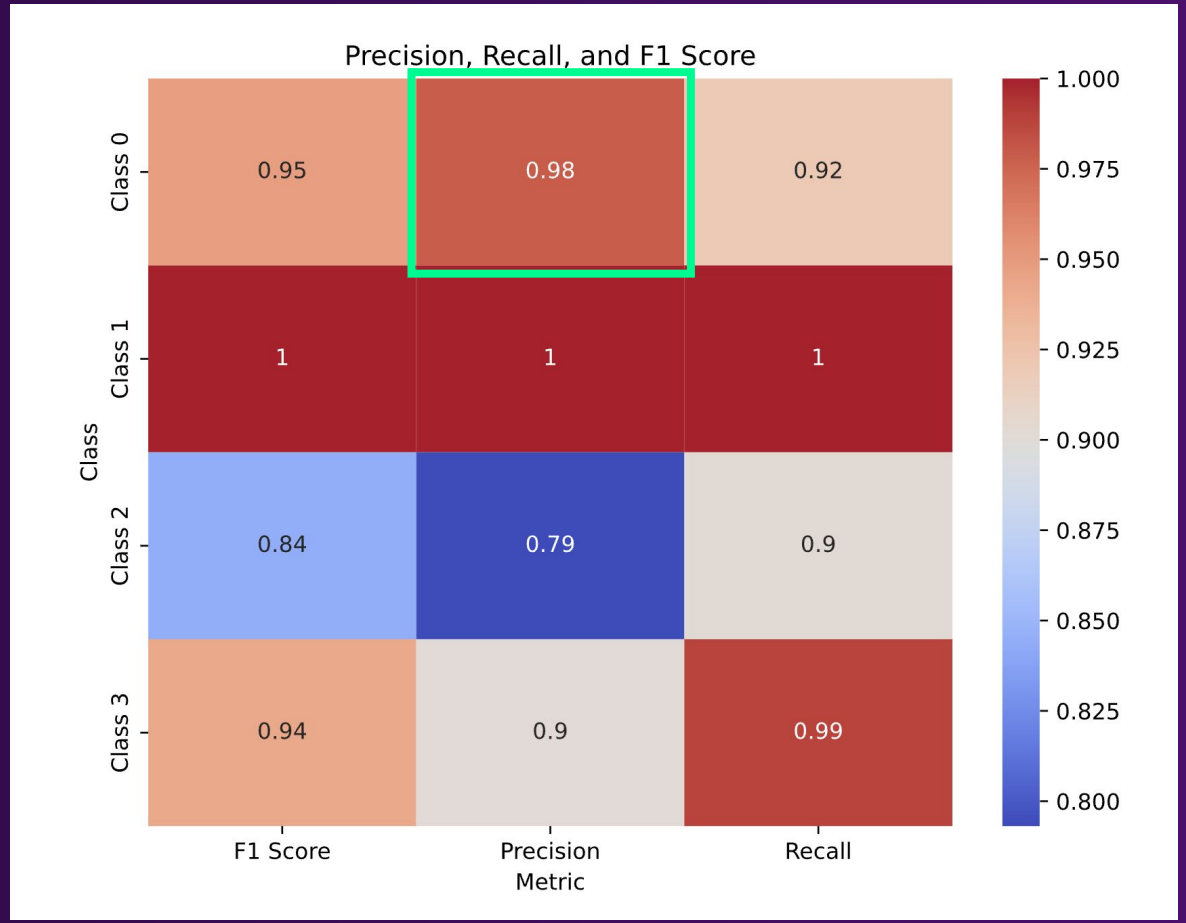




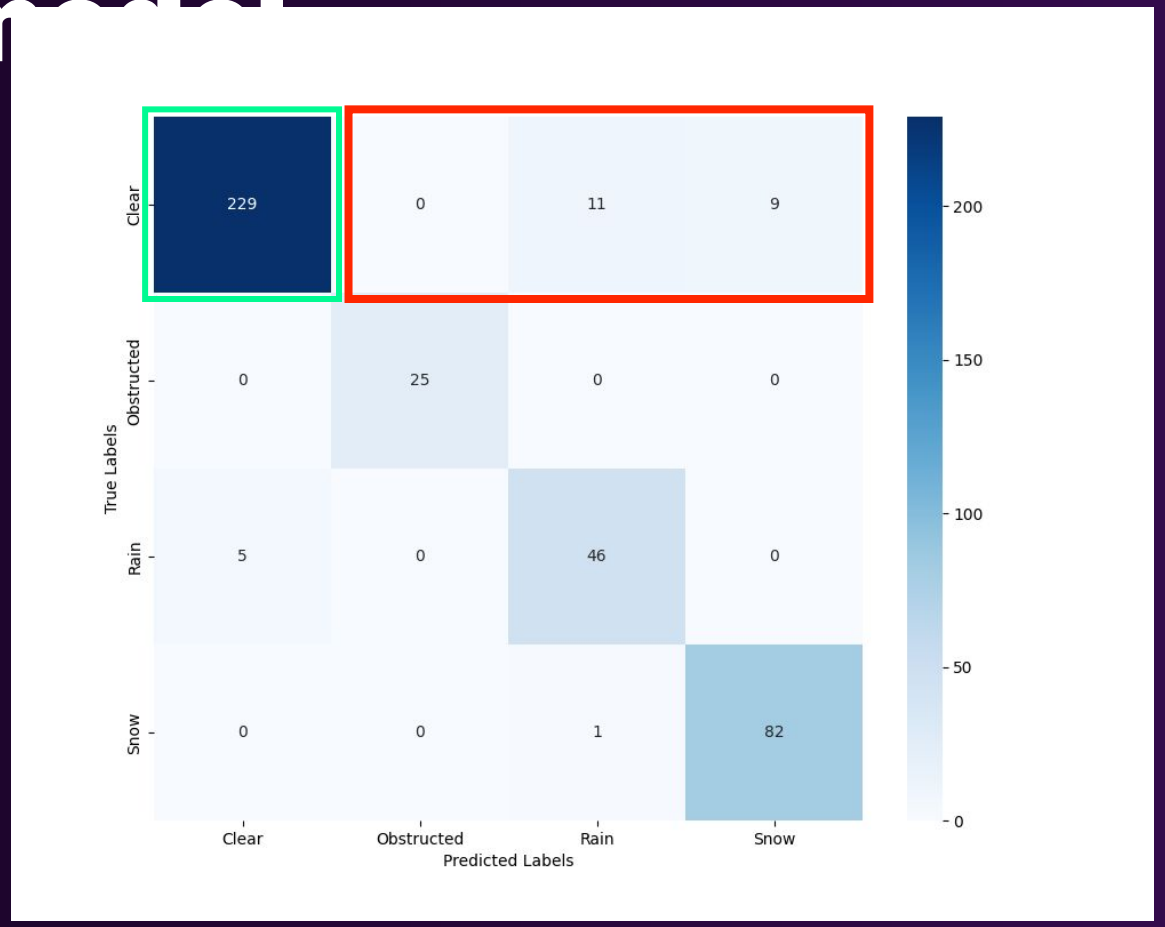
- Dataset: GFAL
- 400 Epochs
- Optimizer: SGD
- Learning Rate: 0.001
- Batch Size: 32

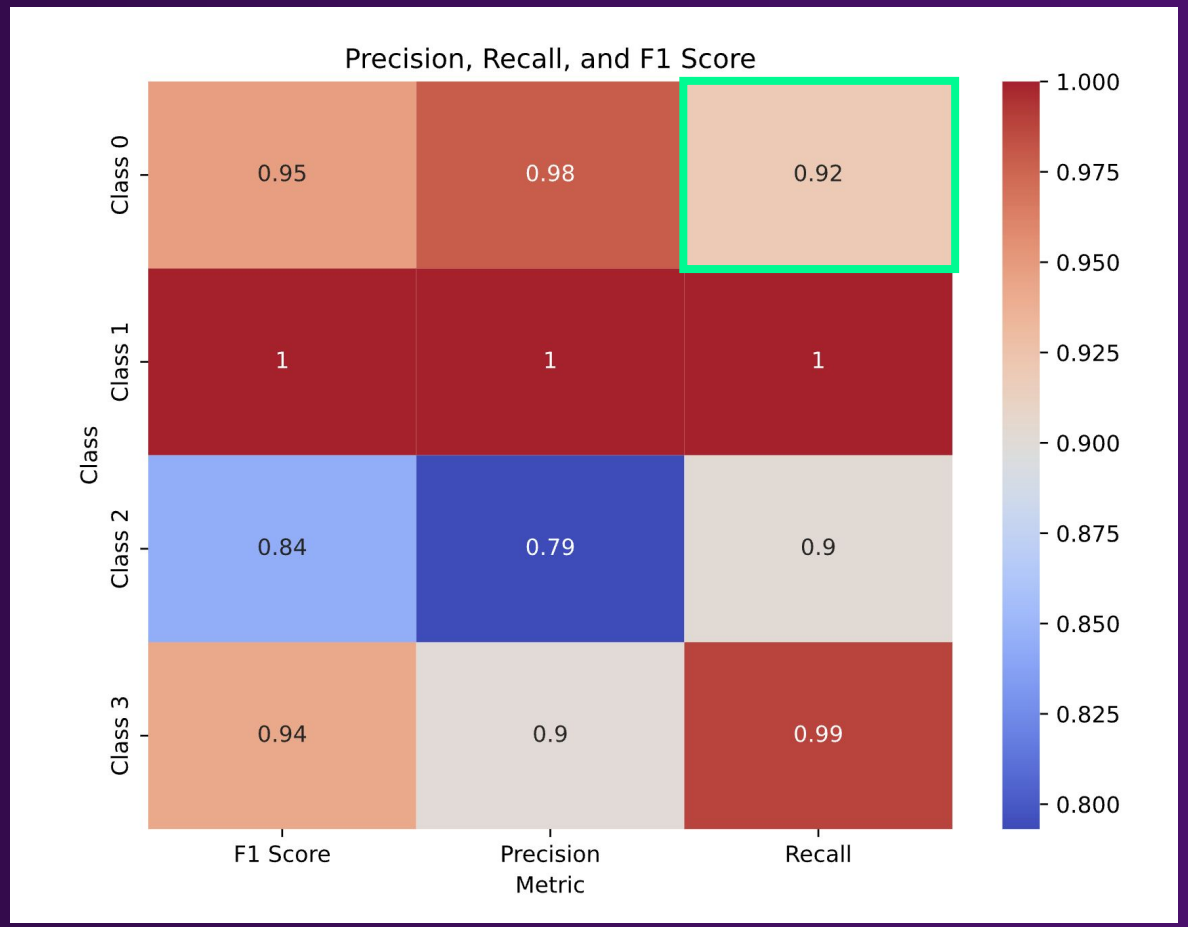
Evaluating the skill of the single site model



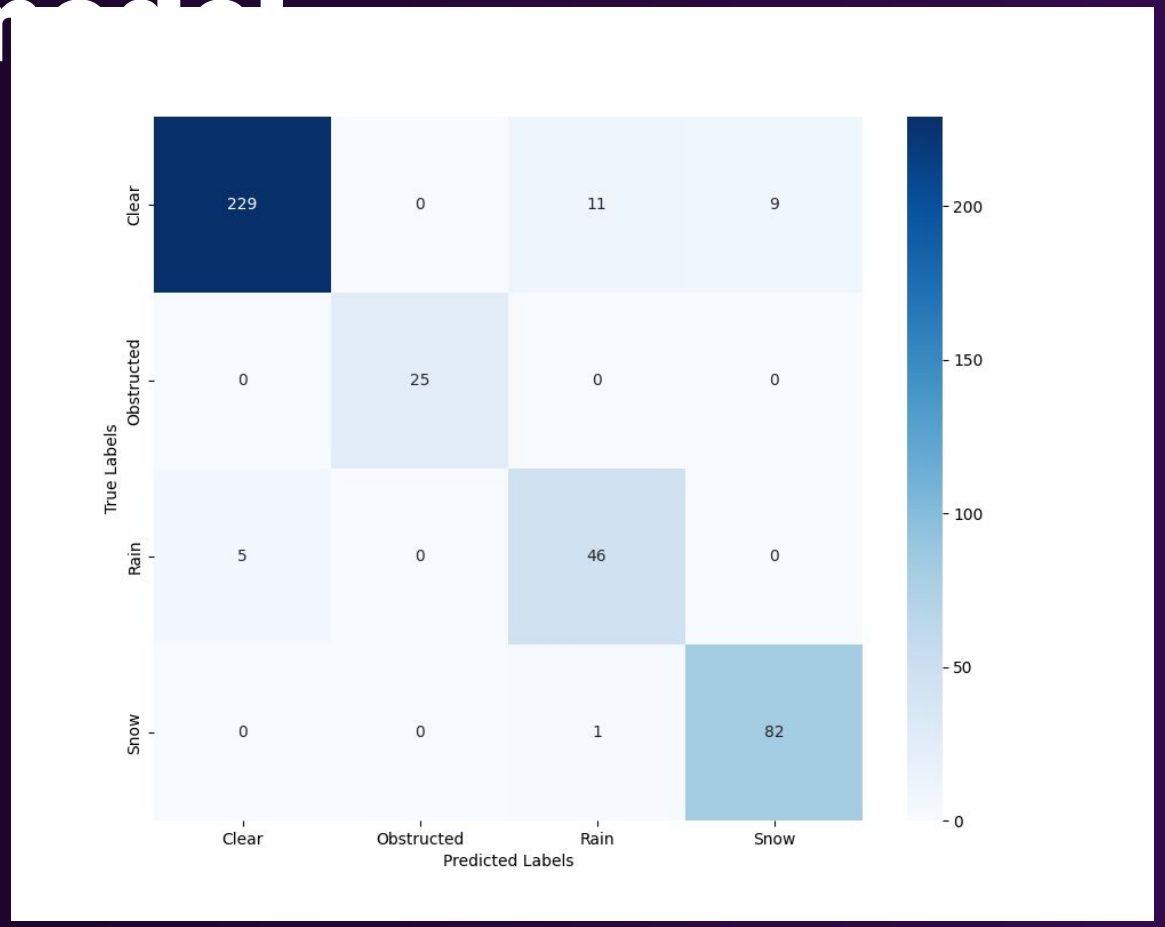


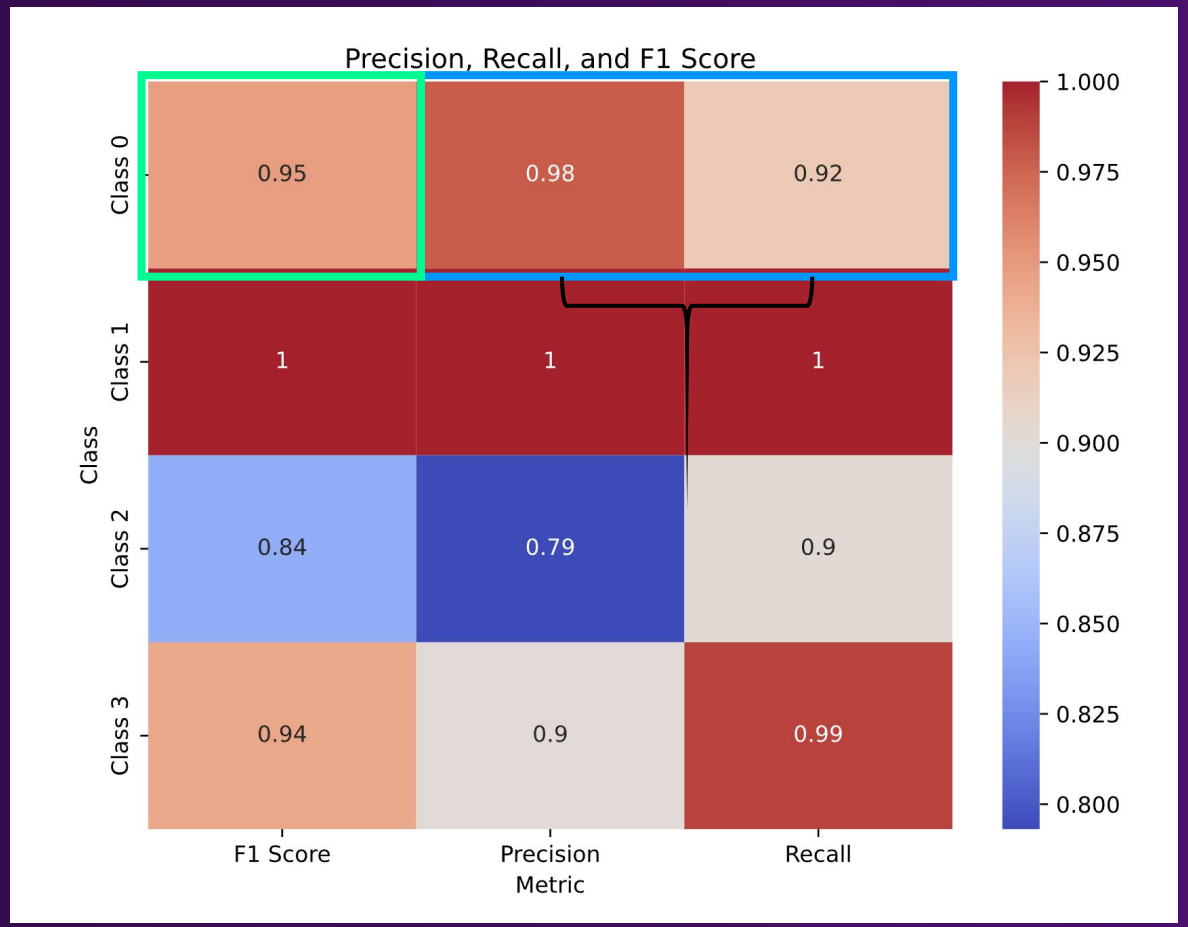
Evaluating the skill of the single site model



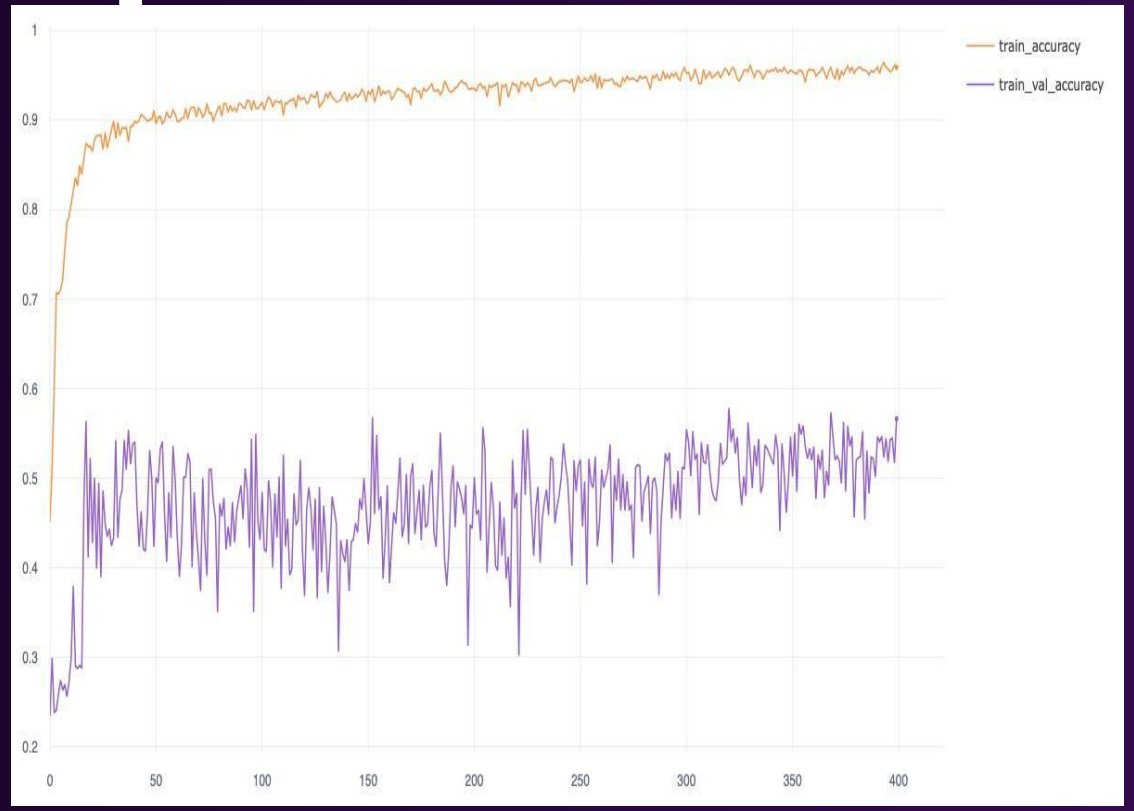


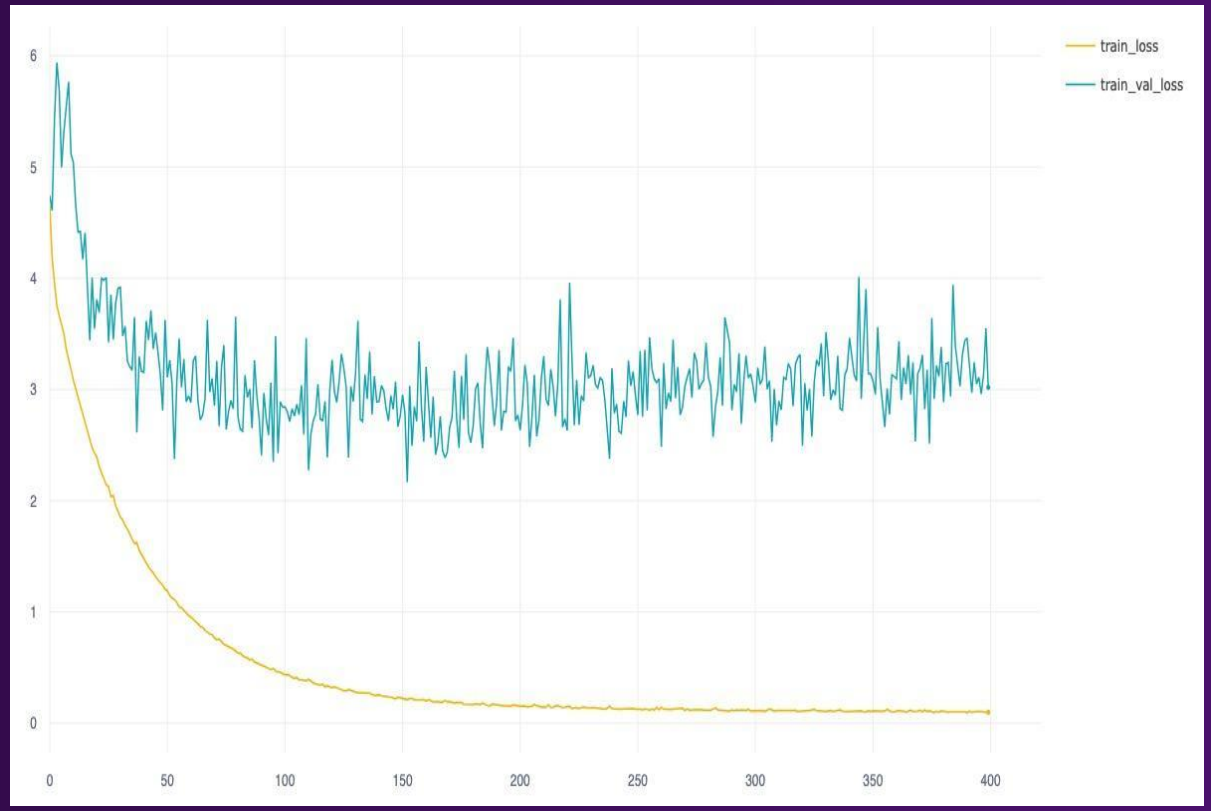
Evaluating the skill of the single site model





Machine Learning – Site Specific Split





Evaluating the Skill

confusion-matrix.json Step 25600/25600

Predicted Category

Actual Category	Snow	Rain	Clear	Obstructed
Snow	15	7	10	499
Rain	93	153	236	51
Clear	58	161	1.40k	213
Obstructed	0	18	0	194

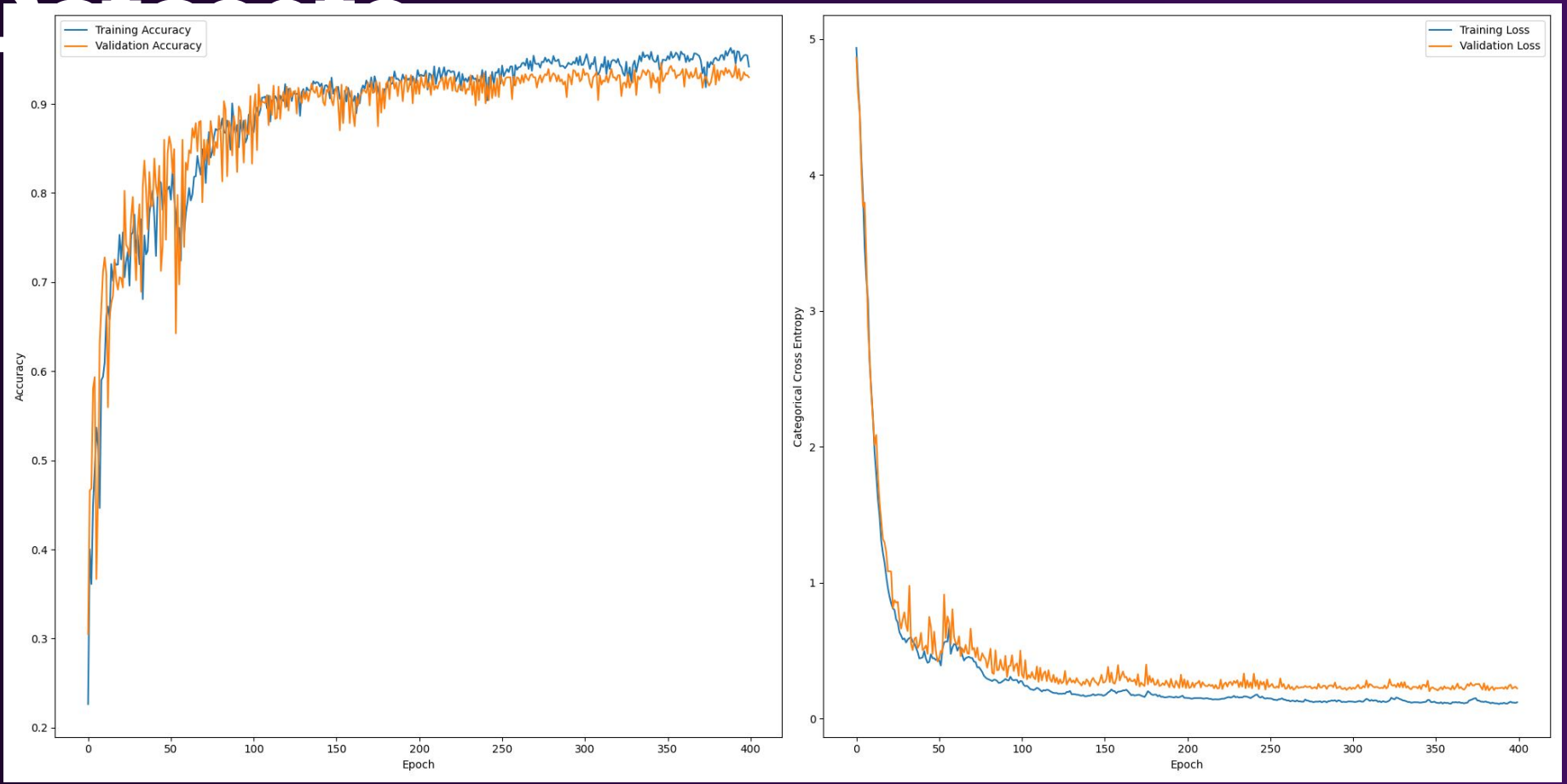
True: Clear, Pred: Obstructed

True: Clear, Pred: Clear

True: Snow, Pred: Snow

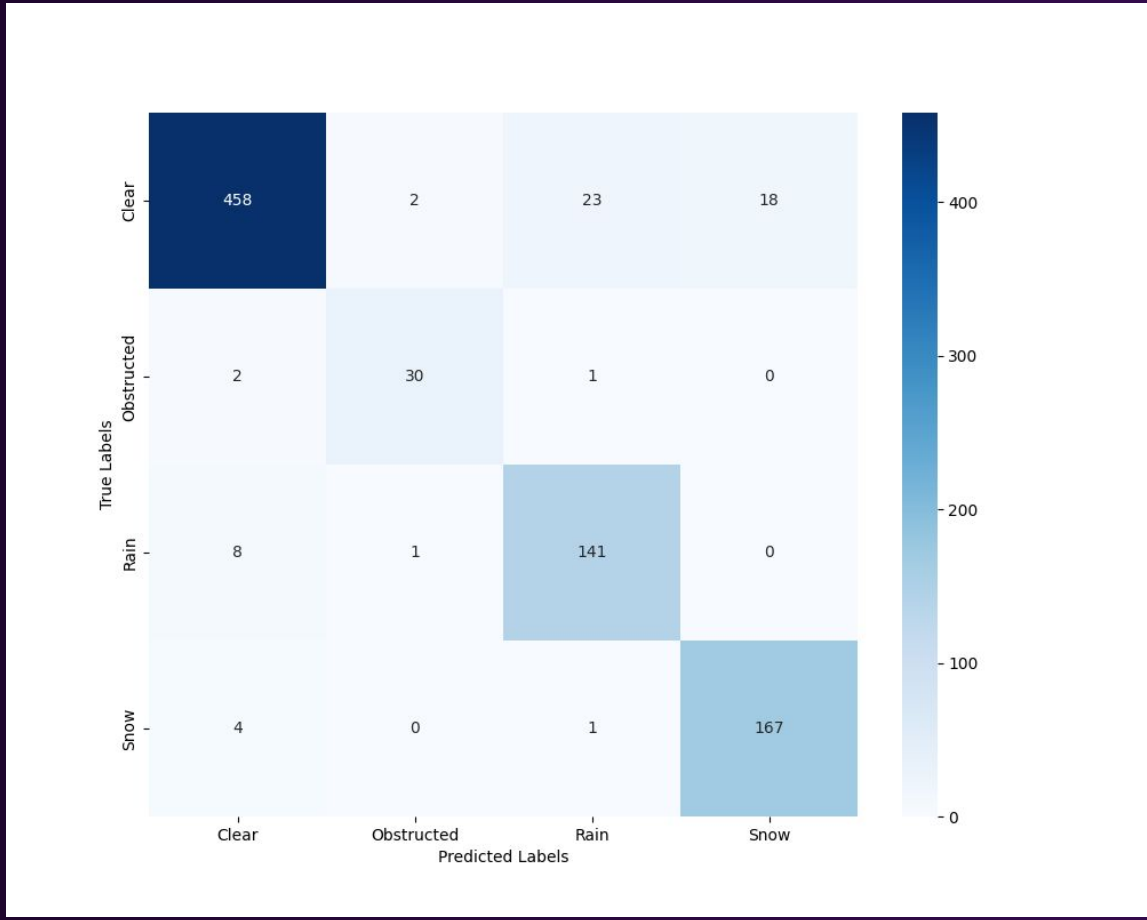
True: Snow, Pred: Obstructed

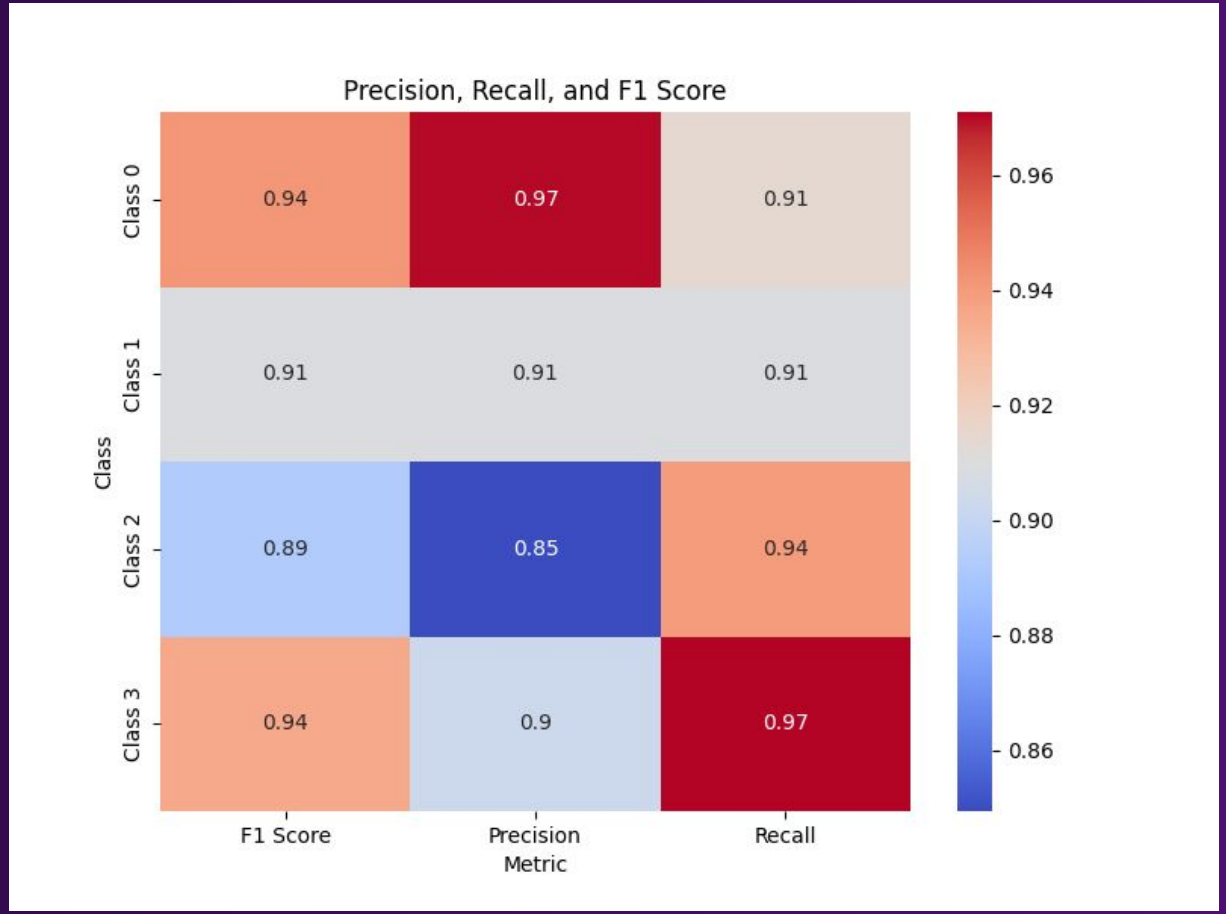
Machine Learning – Combined Datasets



- Dataset: GFAL + ELMI Combined
- 400 Epochs
- Optimizer: SGD
- Learning Rate: 0.001
- Batch Size: 128

Evaluating the skill





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Technical Next Steps

- Increase the generalizability of the Machine Learning model
- Include XAI methods including KernelSHAP, GradCAM, etc. to add explainability to the ML model
- Investigate the ability of the ML model to predict on differenced images

Ultimate Goal

- Create a dashboard that stakeholders can use to monitor camera conditions
- Have an ML model which can generalize all 127 sites cameras with statistically significant accuracy.

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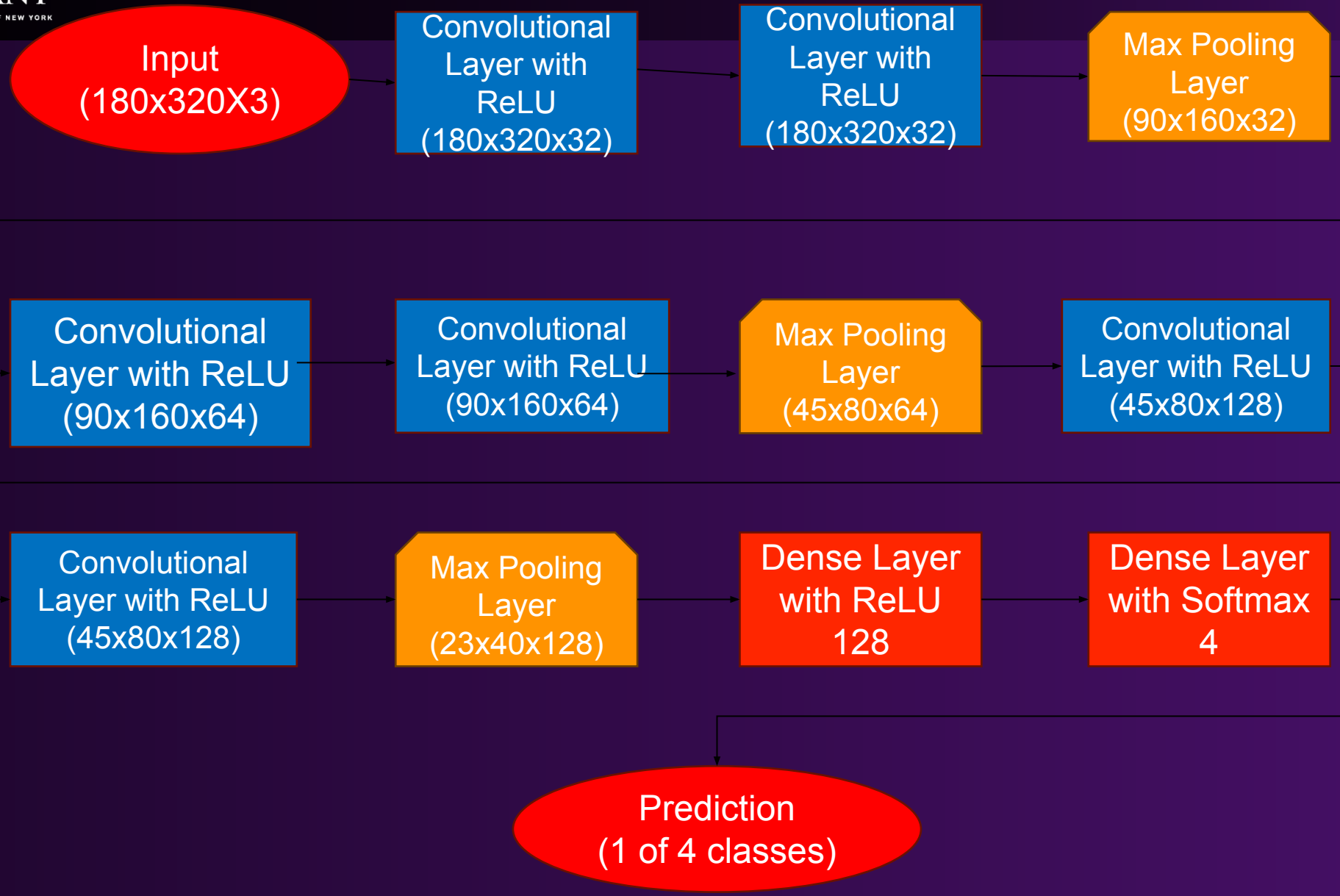
Questions?

- Please feel free to contact me!
  - bthoran@albany.edu


Input
(180x320X3)
Convolutional Layer with ReLU
(180x320x32)
Convolutional Layer with ReLU
(180x320x32)
Max Pooling Layer
(90x160x32)
Convolutional Layer with ReLU
(90x160x64)
Convolutional Layer with ReLU
(90x160x64)
Max Pooling Layer
(45x80x64)
Convolutional Layer with ReLU
(45x80x128)
Convolutional Layer with ReLU
(45x80x128)
Max Pooling Layer
(23x40x128)
Dense Layer with ReLU
128
Dense Layer with Softmax
4
Prediction
(1 of 4 classes)

Hyperparameters

- L2 Regularization – 0.01
- Momentum – 0.99
- Batch Size -32
- Optimizer – SGD
- Image Size – 180,320,3
- Epochs - 400
- Learning Rate – 0.001

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RISE Analysis of incorrect image