





Overview of NYSDOT & SUNY Albany Project:

Automated Detection of Road Conditions from DOT Cameras with AI

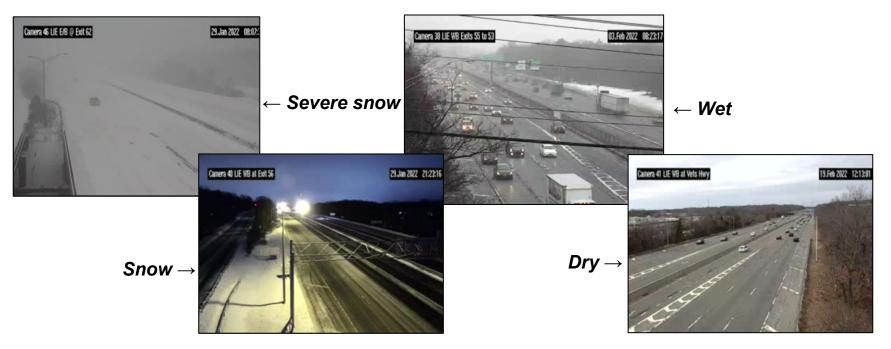
WINTRE-MIX Workshop May 22, 2023

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Motivation

Identify road surface conditions from images using machine learning methods



Data source: camera images above are from the New York State Department of Transportation (NYSDOT), publicly available at 511 ny.org

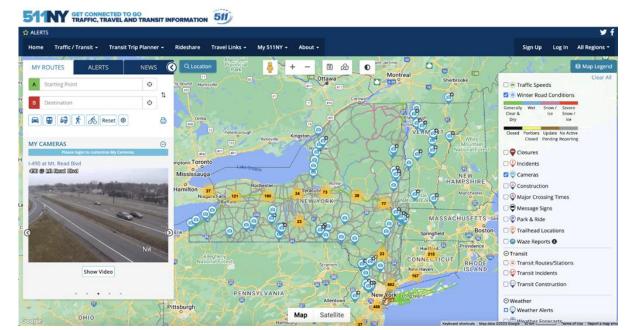


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Data Source

Data source: New York State Department of Transportation (NYSDOT)

Public live cameras: available at 511NY.org

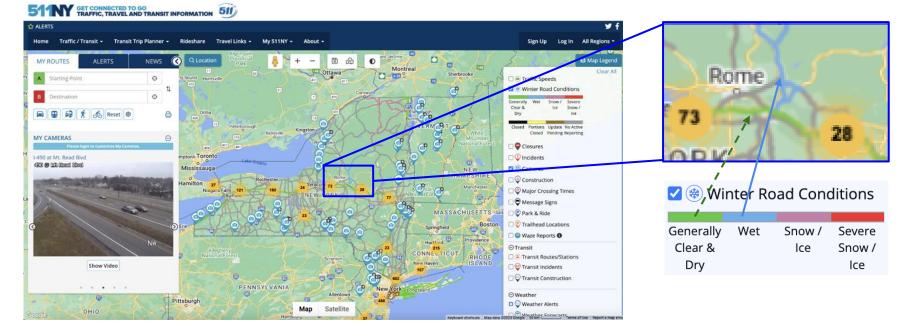






Classification of Winter Road Conditions

Machine learning (ML) models can help make predictions about road surface conditions to aid current classification approaches





Data Archive

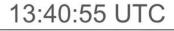
UNIVERSIT ATALBANY State University of New Yor

Archive of camera images starting late January 2022 in UAlbany's xCITE lab

Image snapshots saved out every 5 minutes from 2400 camera sites

Example of two Buffalo images 5 minutes apart











Modeling - Big Picture

Gather image data

Label the data (categorize data into distinct categories, human labeled)

Use the labeled data to build a model (AI/ML)

Determine effectiveness of model

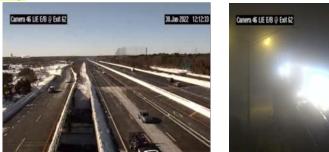




Classification of Road Surface Condition - 6 classes



Dry







The 4 main classes are highlighted and align with DOT WTA (Winter Travel Advisory): https://www.dot.ny.gov/wta/status-definitions

Hand-Labeled Dataset

Mesonet

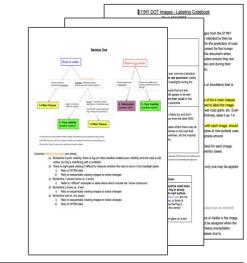
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Labeling "codebook" developed with social scientists:

- ⇒ Carefully define & set rules for labeling to ensure consistency within this project and reproducibility for future projects
- ⇒ Works to increase trustworthiness in the ML model development process Collaboration with NYSDOT:
 - 4 main WTA classes as used on 511ny.org
 - Labeling rules established based on what can **reasonably be determined in images**

High quality weather stations used

to aid in labeling decision making



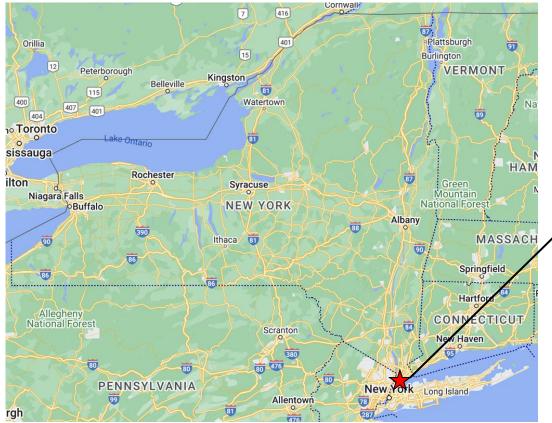


Labeled Images

Location	Num sites	Num imgs	Num classes	Selected some high quality
Bronx	2	4000	3 class) cameras where road surface
Ontario	1	2100	3 class	is visible at night and day
Rochester	1	2900	3 class	Image labeling iterations:
Buffalo (a)	1	1700	3 class	Past codebook versions
Queens	1	1400	3 class	with 3-classes
Rensselaer	1	2000	3 class	
Chatham	1	2000	3 class	Final codebook with 6- classes
Long Isl Expy.	20	10,000	6 class	
Buffalo (b)	1	3,400	6 class ⁽¹⁾	
Total	29	29,000 ⁽²⁾	multiple	(1) no poor visibility or obstructed occurred yet in samples(2) 28000 when including only 3-class: snow, wet, dry



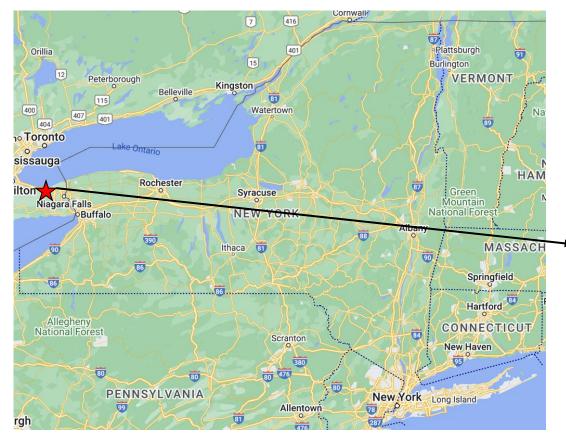












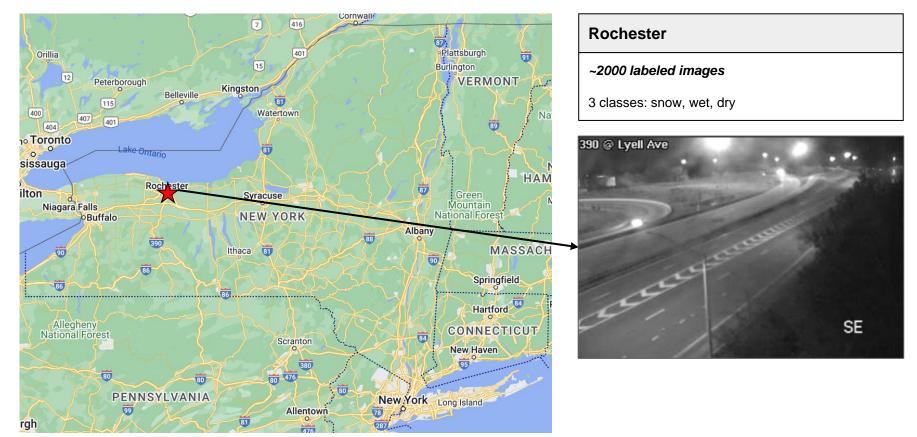
Ontario (St. Catherines) ~2100 labeled images

3 classes: snow, wet, dry









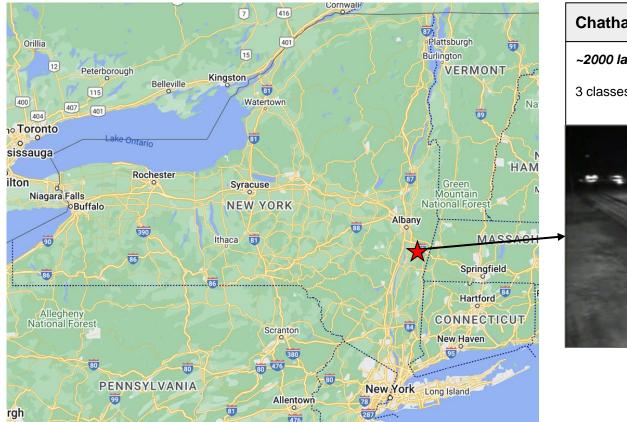


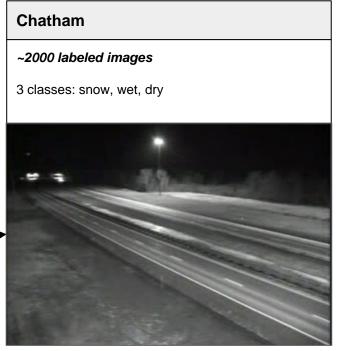






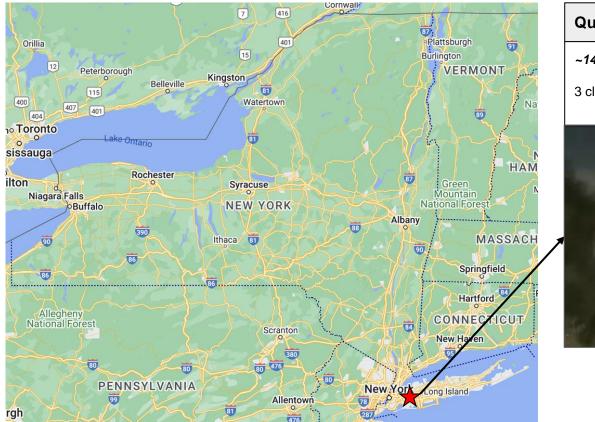


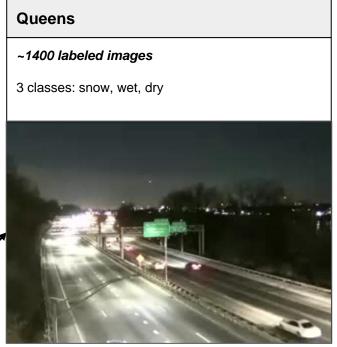






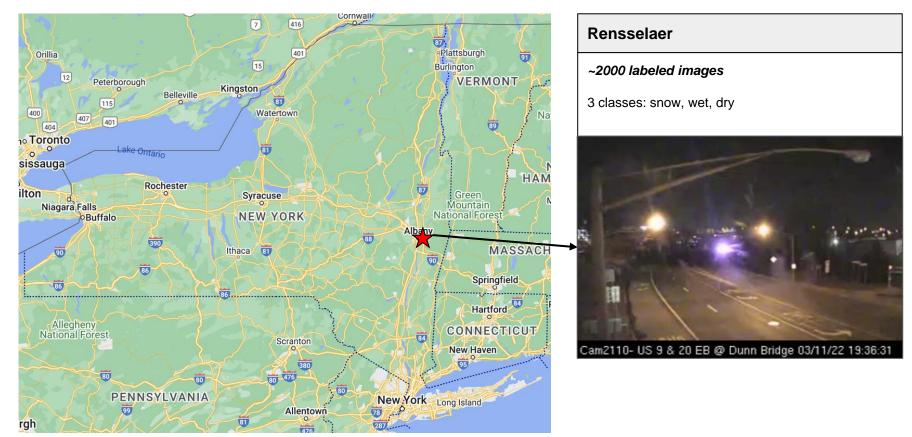






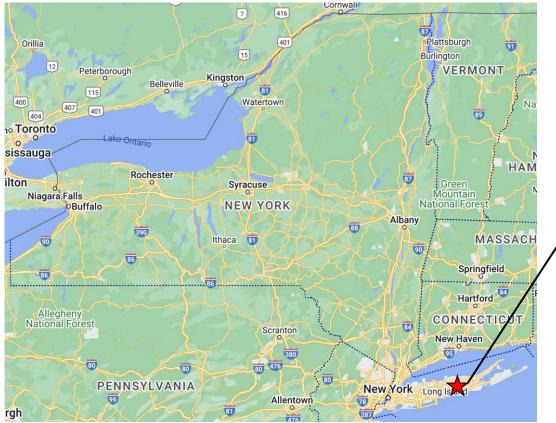


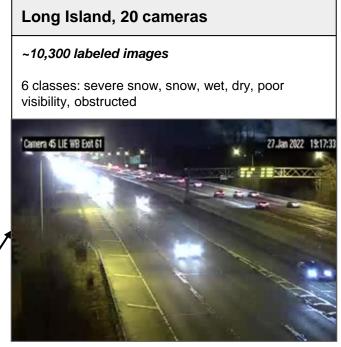


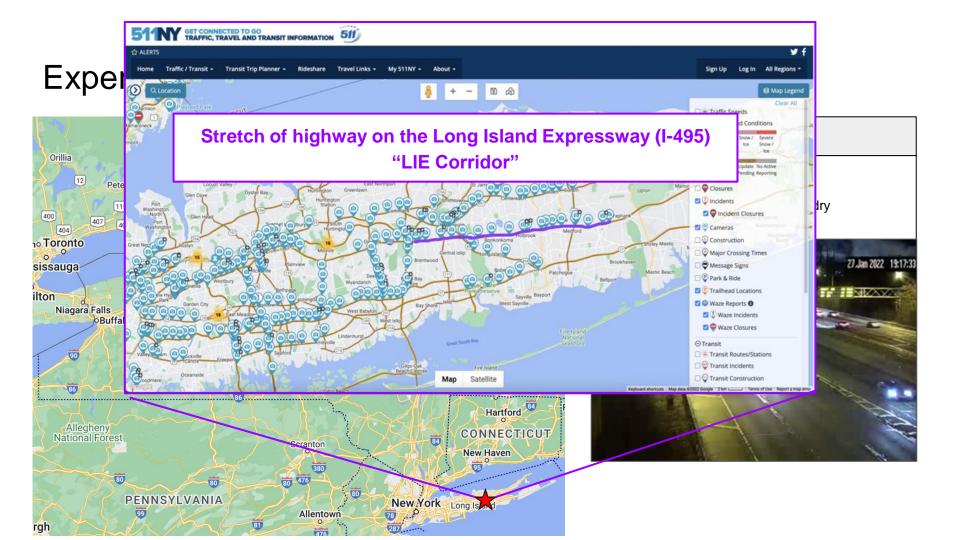








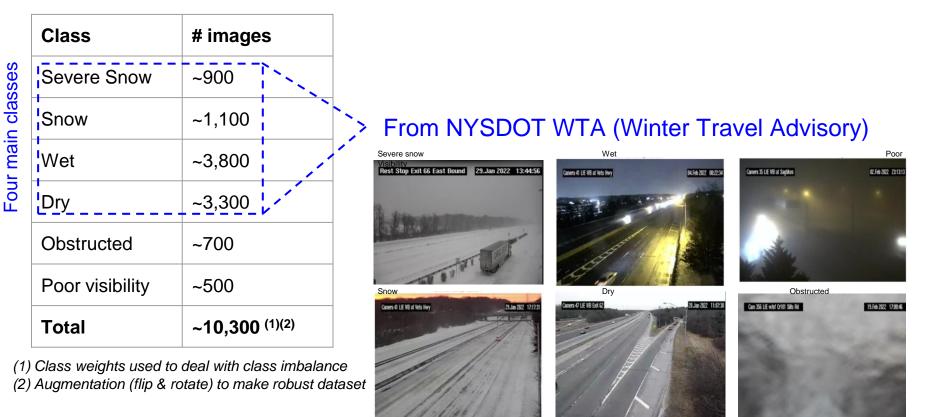








Long Island Expressway (LIE) Labeled Images







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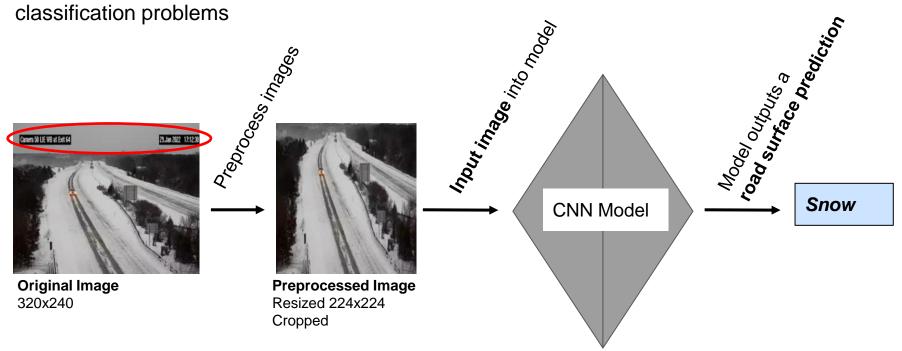
Determine effectiveness of model





Preprocessing & Modeling

Convolutional Neural Networks (CNNs) are ML algorithms commonly used for image classification problems







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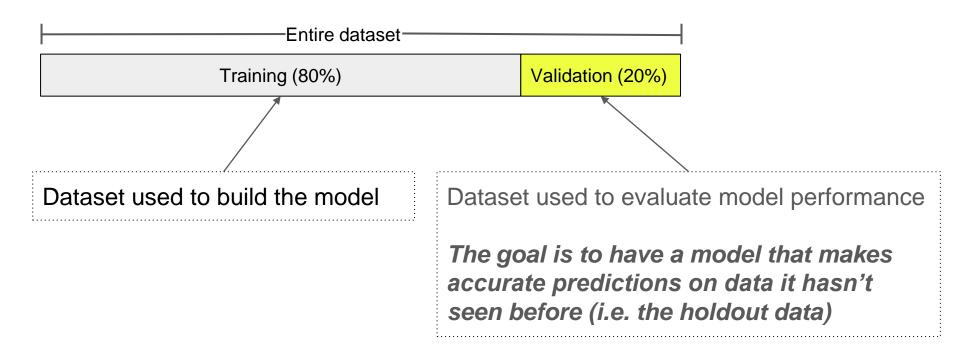
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Data splits

Assess performance of models using a validation (aka "holdout") dataset





Model Successes

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Data split method 1: all 20 sites are represented in both training and validation

Class	Severe snow	Snow	Wet	Dry	Poor Visibility	Obstructed	Average Accuracy		
Correct⁽¹⁾ % (model label = human label)	94.70%	91.80%	91.60% 	94.10%	89.00%	92.90% ▶	92.60%		
(1) Metric shown is recall (out of total labeled in that class). Calculation is recall = probability of detection (POD) = True Positive / (True Positive + False Negative)									
Most commonly misclassified as <i>snow</i>			Most commonly misclassified as		Most co	· ·	•••••••••••••••••••••••••••••••••••••••		
	Most comm misclassifie severe sn	ed as	poor visibility or dry	Most commonly misclassifie as wet	ed	rted r	Most commonly misclassified as <i>poor vis</i> or <i>dry</i>		

:....





Examples

Correct Prediction

actual label snow_severe model predicted snow_severe dry 0.1%, wet 0.6%, snow 12.7%, sev snow 71.0%, obs 0.8%, viz 14.8%



actual label snow model predicted snow dry 0.3%, wet 0.1%, snow 76.2%, sev snow 22.8%, obs 0.6%, viz 0.0%



Incorrect

actual label snow severe model predicted snow dry 0.0%, wet 0.1%, snow 72.3%, sev snow 27.5%, obs 0.0%, viz 0.0%



actual label snow model predicted snow_severe dry 0.0%, wet 0.2%, snow 40.8%, sev snow 58.9%, obs 0.0%, viz 0.0%



Severe snow

Snow





Examples

Correct Prediction Attal label wer model predicted wer (by 0.0%, wet 100.0%, snow 0.0%, sev snow 0.0%, obs 0.0%, viz 0.0% (b) Correct Correct Rest Aves (c) Correct

actual label dry model predicted dry dry 38.4%, wet 26.2%, snow 35.1%, sex snow 0.1%, obs 0.1%, viz 0.0%





actual label dry model predicted wet dry 38.5%, wet 61.4%, snow 0.0%, sev snow 0.0%, obs 0.0%, viz 0.0%



Wet

Dry





Examples

Correct Prediction

actual label poor_viz model predicted poor_viz dry 0.8%, wet 17.6%, snow 0.2%, sev snow 1.5%, obs 27.5%, viz 52.5%



actual label obs model predicted obs dry 0.0%, wet 0.1%, snow 0.0% sev snow 0.3%, obs 89.6%, viz 10.1%







actual label poor viz



actual label obs model predicted poor_viz dry 0.0%, wet 0.4%, snow 0.0%, sev snow 0.0%, obs 47.7%, viz 51.8%



Poor Visibility

Obstructed



Model Difficulties

Data split method 2: unique sites in training vs validation

- 16 sites in training
- 4 sites in validation (holdout)

Model accuracy about ~70%

⇒ An important problem to fix because we want the model to generalize well to unseen sites across the state





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Summary

ML model performs well on data it's "seen"

Example:

If model is trained on Site A and Site B, it will perform well on Site A and Site B

 \Rightarrow A matter of having labeled data

ML model needs improvement on data it's never seen

Example:

If model is trained on Site A and Site B it won't perform very well on Site C

 \Rightarrow An open-ended algorithm development/computer science question



Future Work

Drivin by goal of model generalizability:

- Labeling
 - Have winter 2022-2023 season images to include
 - Labeling working group to label images, adding thousands more images across new sites
- Improving model architecture

Thank you!

Contact for questions or comments: Carly Sutter <u>csutter@albany.edu</u>, Nick Bassill <u>nbassill@albany.edu</u>, Kara Sulia <u>ksulia@albany.edu</u> This material is based upon work supported by the National Science Foundation under Grant No. ICER-2019758





Appendix

Two Methods for Train/Val Data Splitting

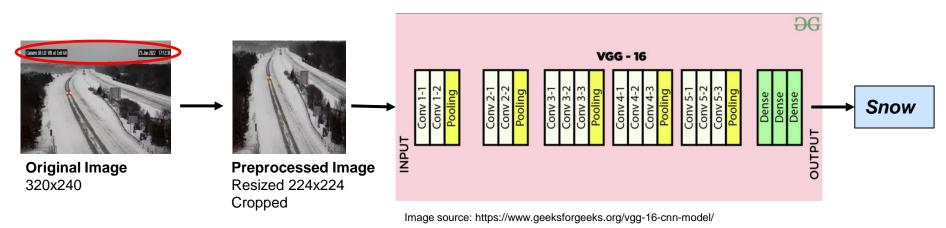
Cam #	All sites in training and validation High accuracy model >92%						
1	Training	Val					
2	Training	Val					
3	Training	Val					
4	Training	Val					
5	Training	Val					
6	Training	Val					
7	Training	Val					
8	Training	Val					
9	Training	Val					
10	Training	Val					
11	Training	Val					
12	Training	Val					
13	Training	Val					
14	Training	Val					
15	Training	Val					
16	Training	Val					
17	Training	Val					
18	Training	Val					
19	Training	Val					
20	Training	Val					

Site-specific validation
Model accuracy ~70%
Training
Val
Val
Val
Val

Preprocessing & Model Details

Convolutional Neural Network (CNN)

Using VGG16 architecture



More Model Details

Python Package:	Loss function:	Optimizer:	Learning Rate:	Activation function:	Epochs:
Tensorflow	Categorical Cross Entropy	SGD	0.01, exponential decay rate 0.99	Relu Softmax (output layer)	Max 50 Early stopping 10

Other modeling details

Image data generator

5-fold cross validation used

Updates made from last meeting with DOT in November 2022:

- Regularization
- Dropout
- Additional image augmentation (brightness temperature

Confusion Matrix

One of the folds from 5-fold CV

	Confusion Matrix fold3 on Val Data									
snow_severe	94.02% 173/184	3.80% 7	0.00% 0	0.00% 0	1.63% 3	0.54% 1			- 80%	
snow	4.29% 9	93.33% 196/210	2.38% 5	0.00% 0	0.00% 0	0.00% 0				
-abel wet	0.00% 0	1.19% 9	91.17% 692/759	1.84% 14	5.40% 41	0.40% 3			-60%	
True Label dry	0.00% 0	0.30% 2	4.63% 31	93.88% 629/670	0.60% 4	0.60% 4			-40%	
poor_viz	0.00% 0	0.00% 0	4.63% 5	0.00% 0	91.67% 99/108	3.70% 4			-20%	
sdo	0.70% 1	0.00% 0	2.10% 3	1.40% 2	5.59% 8	90.21% 129/143			00/	
	snow_severe	snow	wet Predicte	dry ed Label	poor_viz	obs			-0%	

Example of Incorrect Label

Human error in labeling in which case the model did better!

actual label poor_viz model predicted wet dry 0.0%, wet 100.0%, snow 0.0%, sev snow 0.0%, obs 0.0%, viz 0.0%



Experiments to Optimize Image Labeling

Goal of experiments: understand how to optimize time spent labeling images, especially under the lens of generalizability

- Secondary goal: provide perspective on claim that model just "needs more data"

Findings:

1) the focus should be on adding **more sites** rather than more images of existing sites (experiment 3)

2) ~400 images per site is optimal (experiment 2)

3) ~12 training sites per 3 validation sites (15 sites) is ideal (experiment 1b)

