Neural Network for Winter Weather Precipitation Type Prediction

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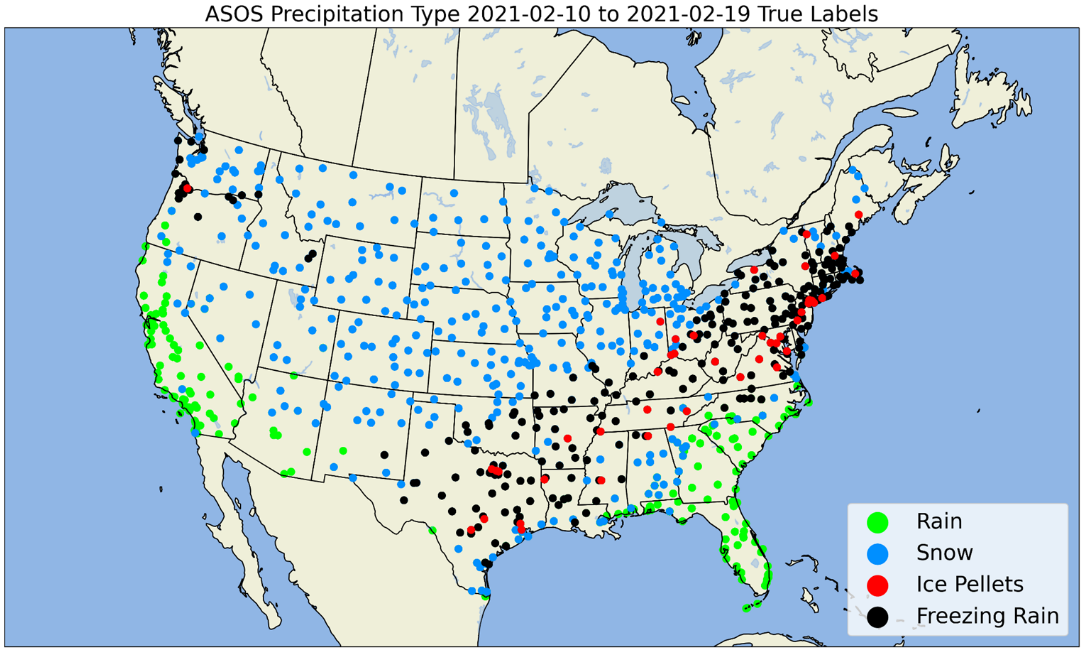
Introduction and Motivation



- An estimated 1.4 million accidents, 600,000 injuries, and 7,000 deaths occur each year due to dangerous conditions caused by winter precipitation on roadways
- It is difficult to predict winter weather with spatiotemporal consistency
- **We want to leverage machine learning techniques to accurately predict precipitation types in winter weather events**

Precipitation Types

Rain

Snow

Ice Pellets (sleet)

Freezing Rain

https://www.farmersalmanac.com/frozen-precipitation-defined-23431

all other images from https://www.weather.gov/jetstream/preciptypes

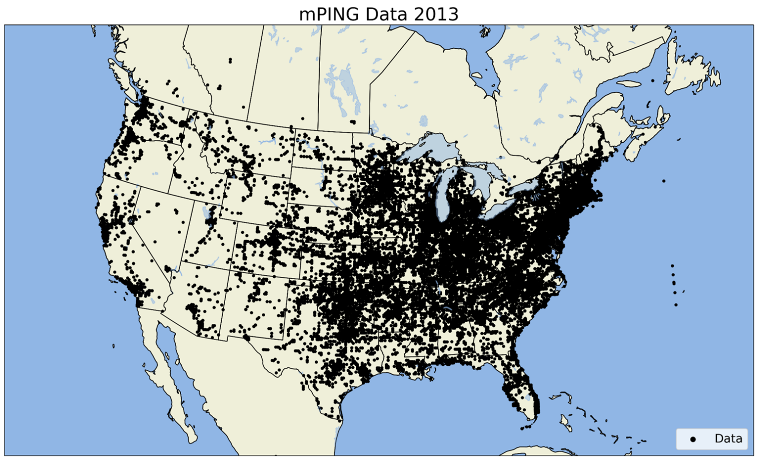
Datasets

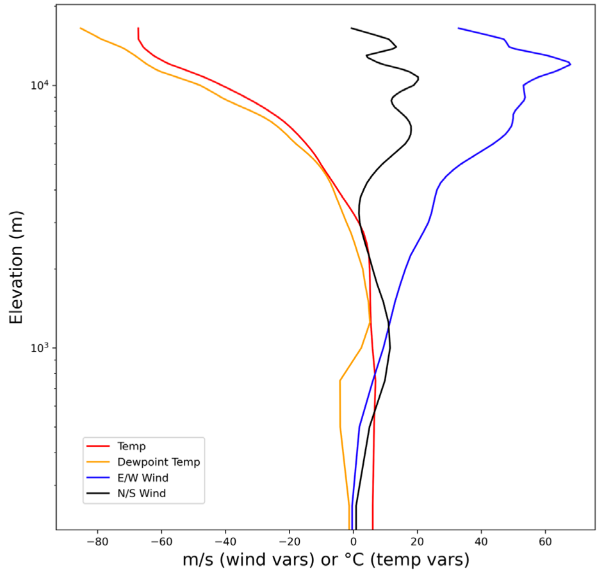
Input Data:

- **RAP:** temperature, dew point temperature, east/west wind velocity, and north/south wind velocity values at various heights in the atmosphere

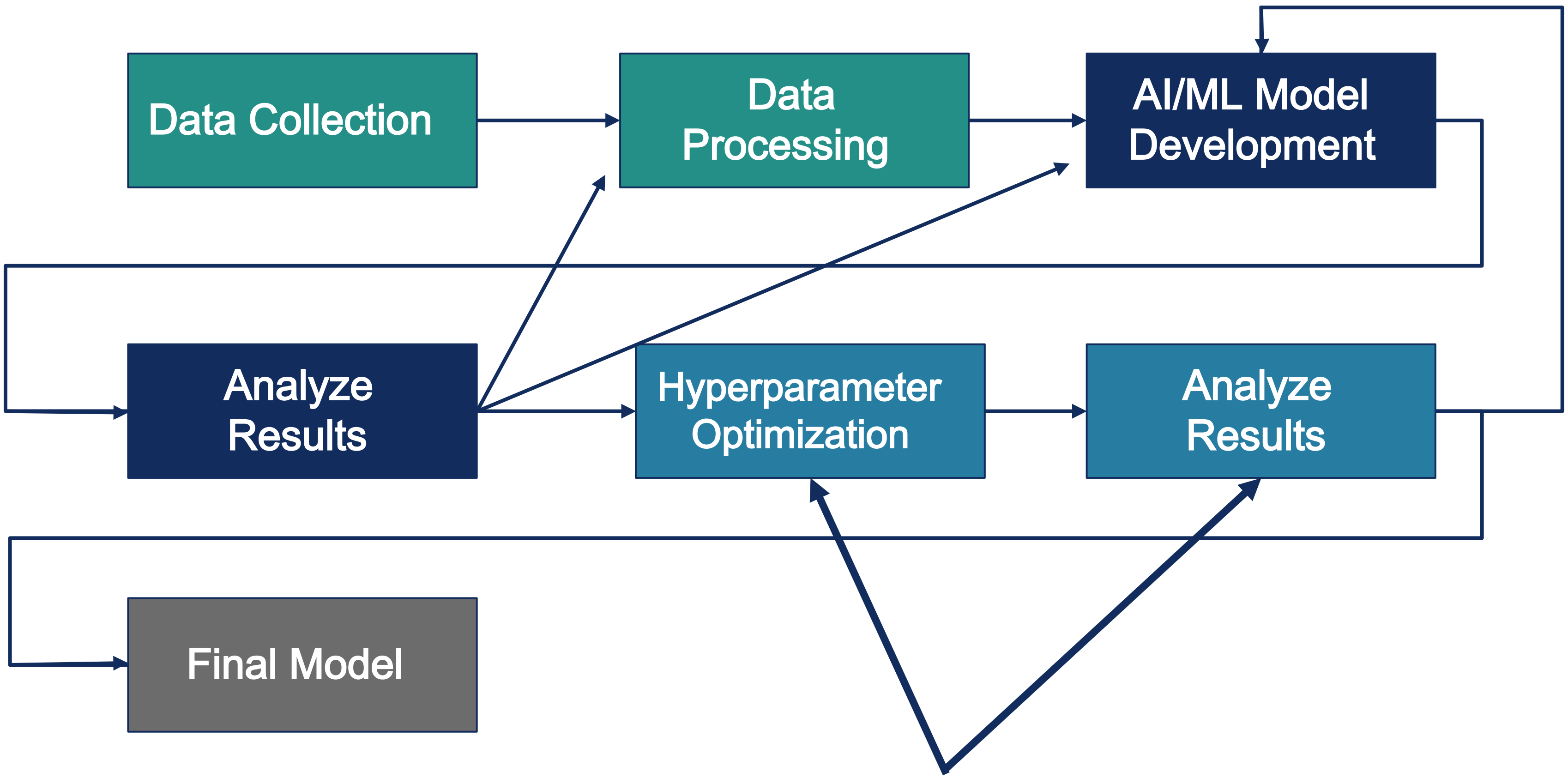
Output Data (observations):

- **ASOS:** system of automated weather reporting stations across the U.S. which report precipitation type
- **mPING:** mobile application where users can submit weather reports, including precipitation type



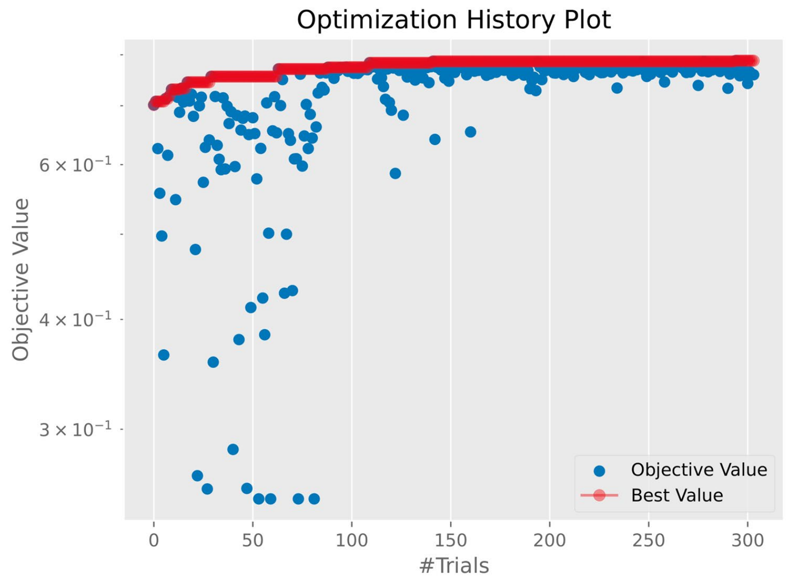


Machine Learning Process



I will focus on this section of the workflow in the remainder of the presentation

Hyperparameter Optimization Overview

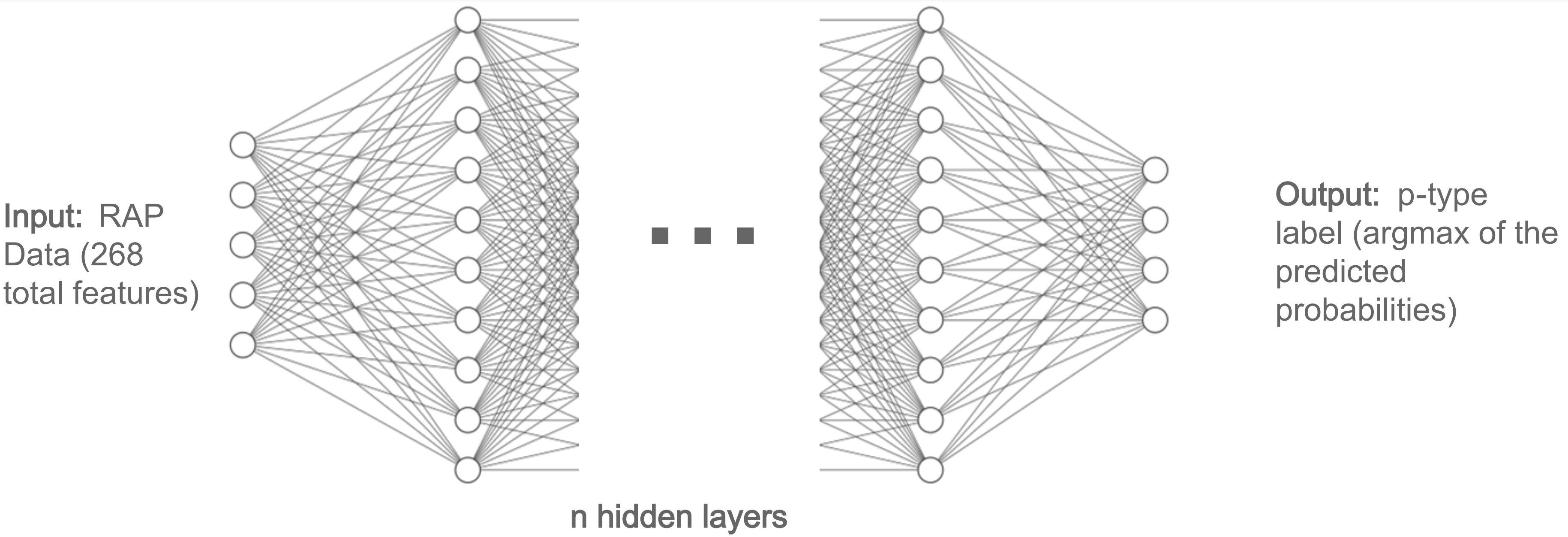


- Process to fine tune the manually set parameters of the model (hyperparameters) to maximize or minimize an evaluation metric

- Conducted using the Earth Computing Hyperparameter Optimization (ECHO) package, a custom package developed within the NCAR AIML group

- **Goal: maximize the average accuracy of the model**

Hyperparameter Optimization Results



ASOS:

Number of hidden layers: 6
Hidden layer size: 534

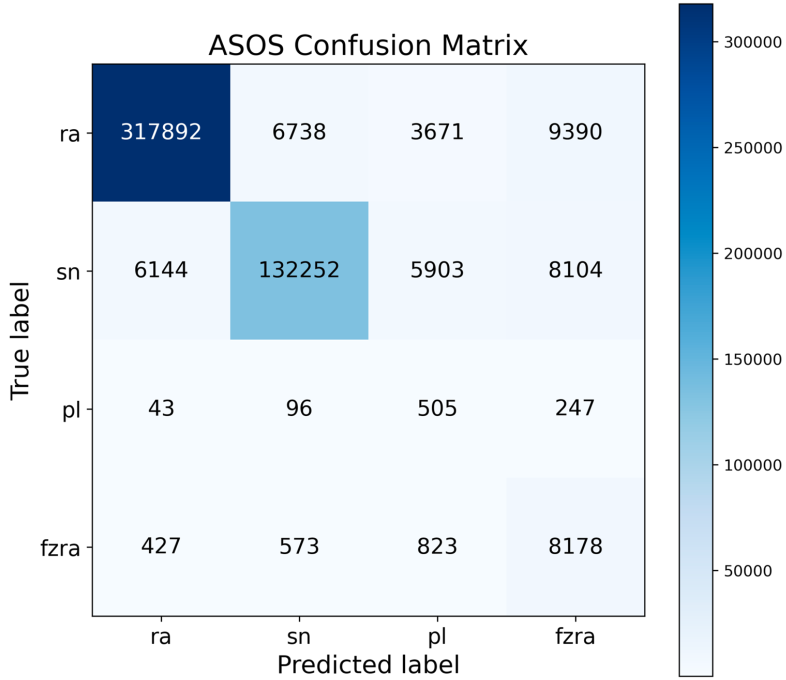
Activation function: ELU
Output activation function: softmax
Loss function: categorical cross-entropy

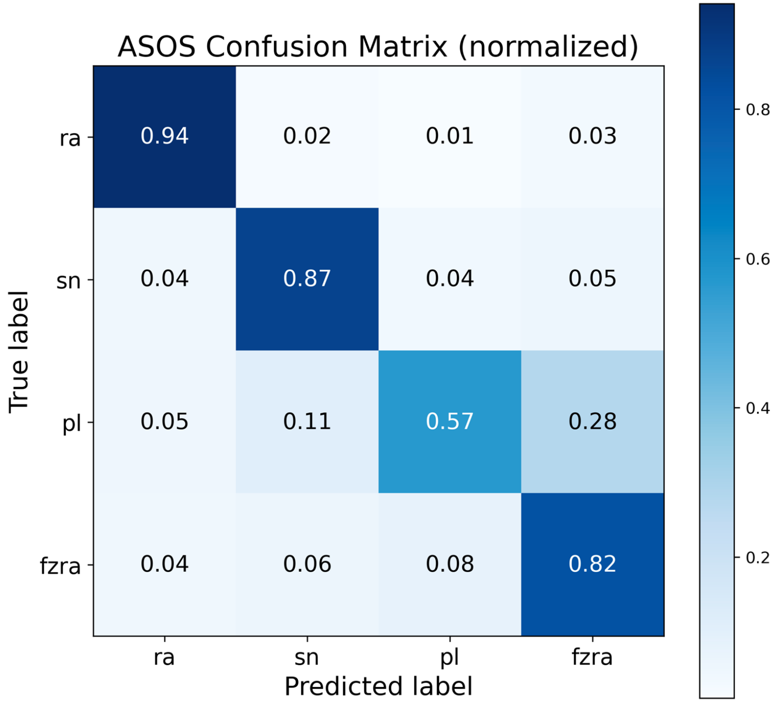
mPING:

Number of hidden layers: 12
Hidden layer size: 105

Activation function: Leaky RELU
Output activation function: softmax
Loss function: categorical cross-entropy

ASOS Confusion Matrices

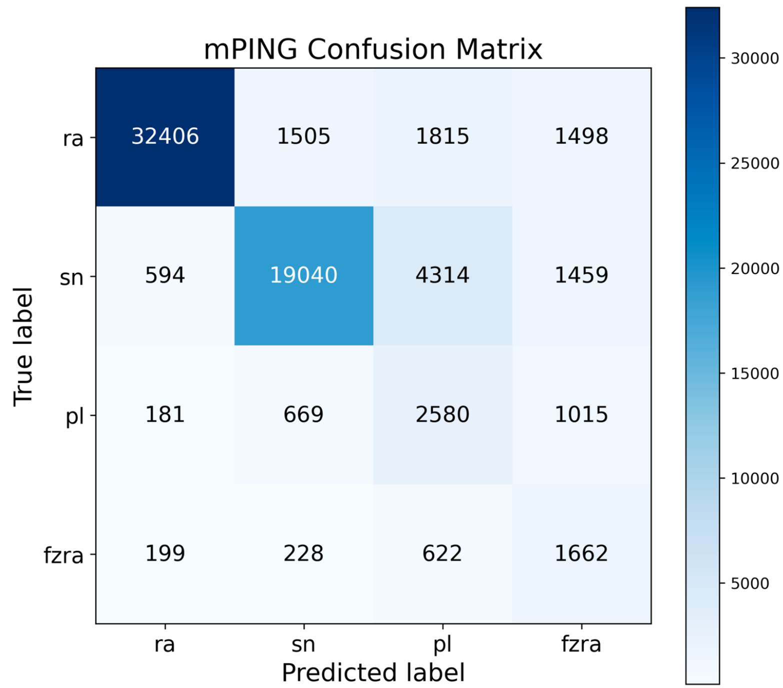


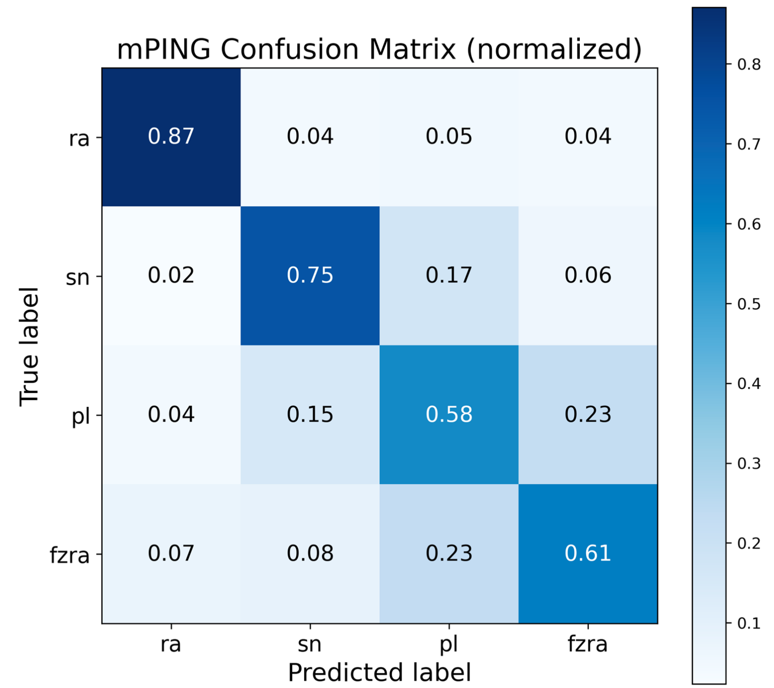


Rain accuracy: 94%
Ice Pellets accuracy: 57%

Snow accuracy: 87%
Freezing Rain accuracy: 82%

mPING Confusion Matrices

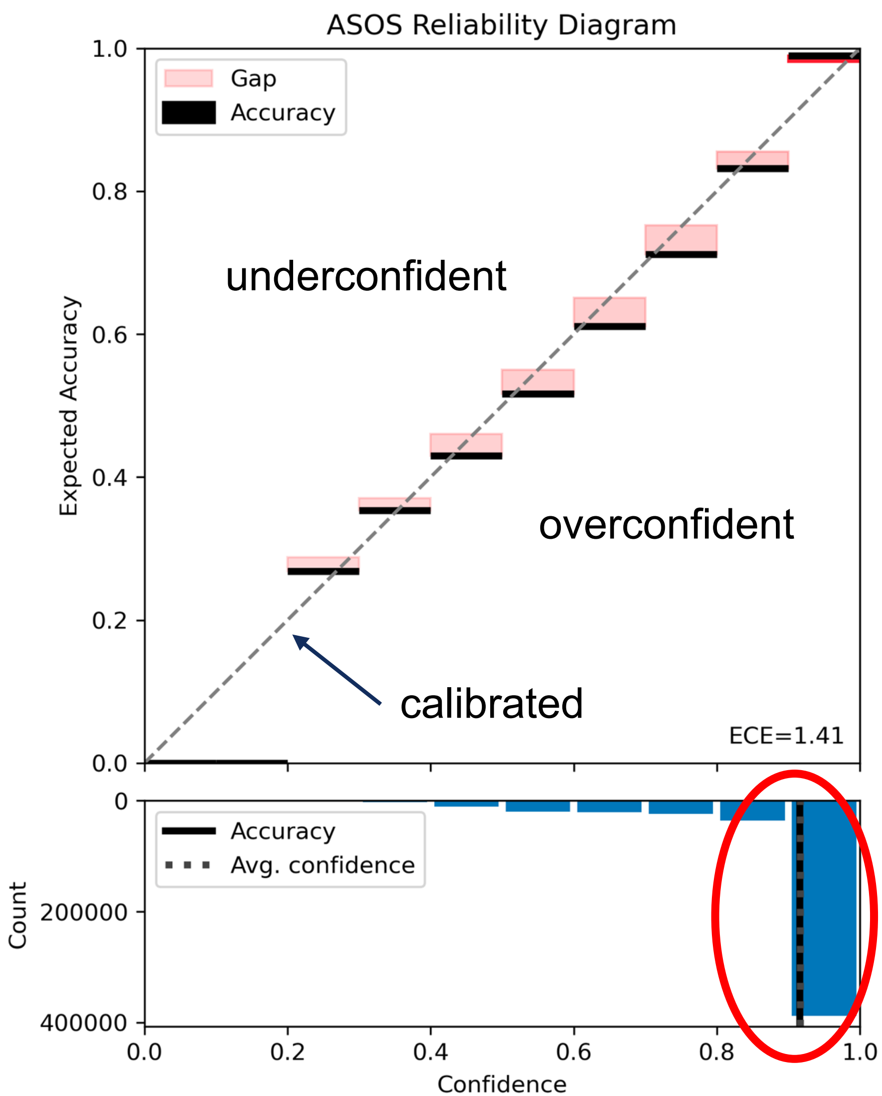




Rain accuracy: 87%
Ice Pellets accuracy: 58%

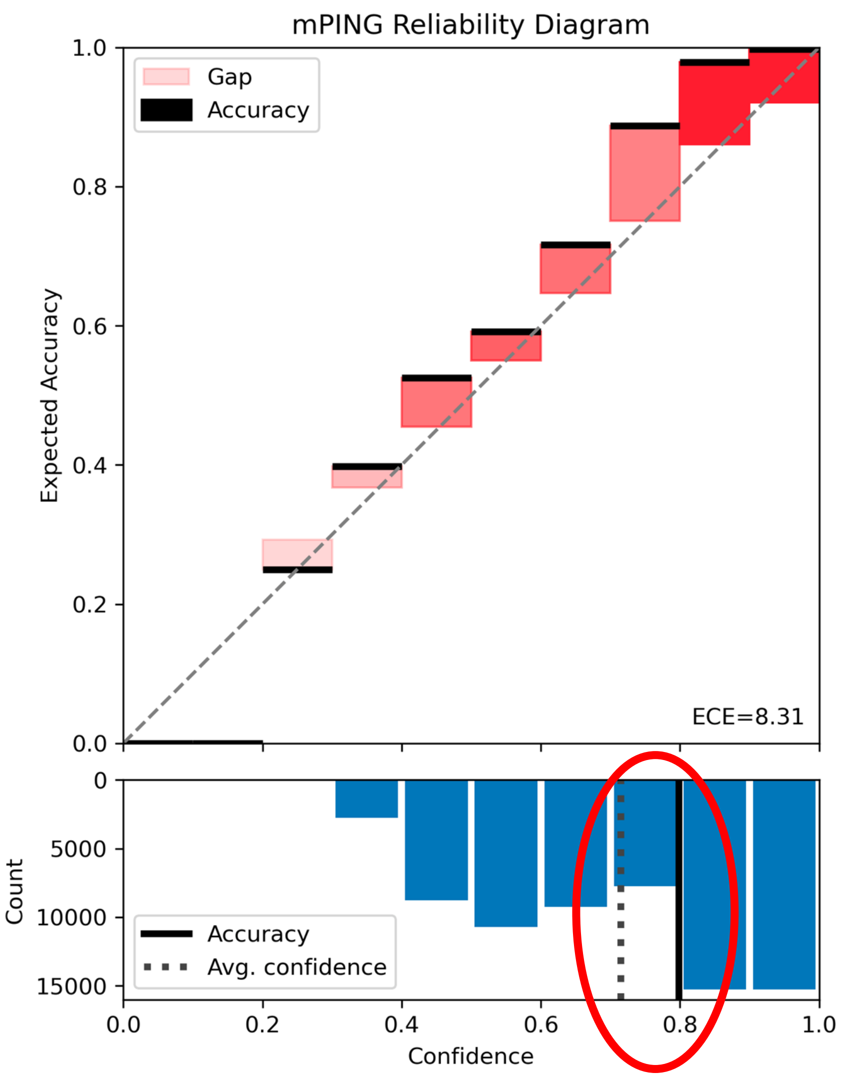
Snow accuracy: 75%
Freezing Rain accuracy: 61%

ASOS Reliability Diagram



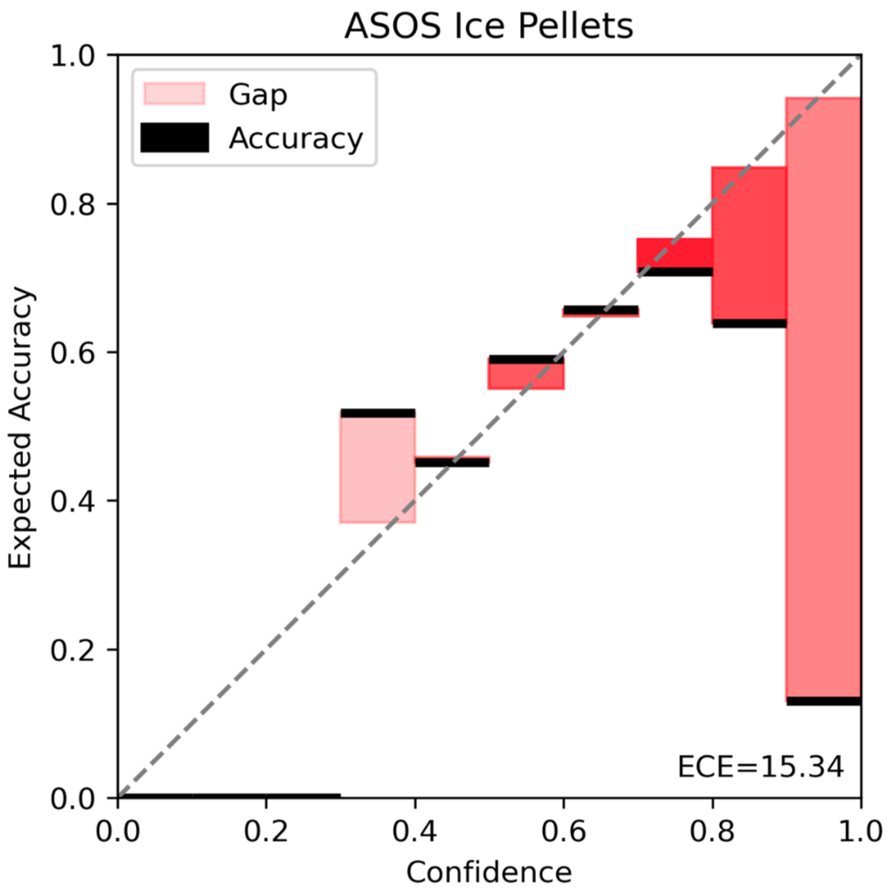
- Expected calibration error (ECE): weighted sum of the deviation of accuracy from the diagonal line
- Indicates whether the model is overconfident, underconfident, or calibrated
- The model has a low ECE and the average confidence is nearly equal to the accuracy (red oval)
- These results suggest the model is calibrated

mPING Reliability Diagram



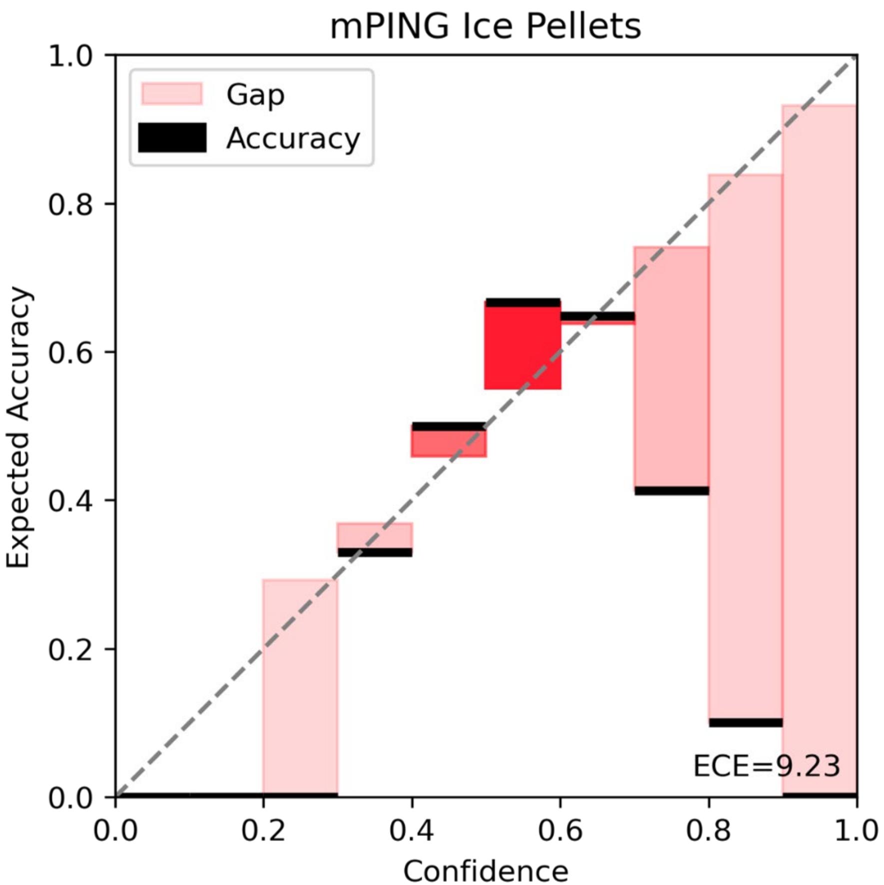
- mPING model had a higher ECE than the ASOS model therefore it was less calibrated
- The model tended to be underconfident (average confidence less than accuracy)

ASOS Ice Pellets Reliability Diagram



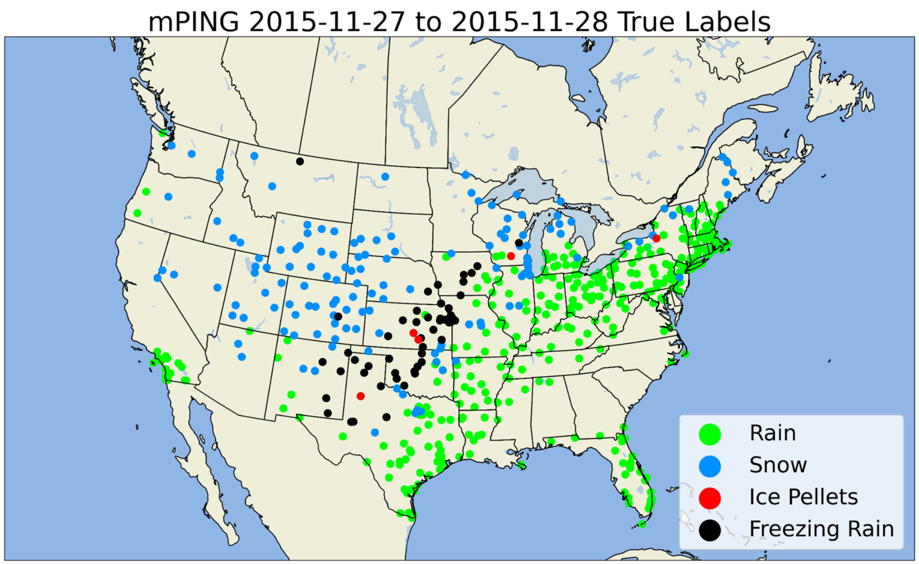
- Rain, snow, and freezing rain had patterns similar to the overall diagram
- Ice pellets become extremely overconfident at high confidences, a concerning trend
- This trend may be caused by biases in the data
- 85% of ASOS stations cannot report ice pellets

mPING Ice Pellets Reliability Diagram

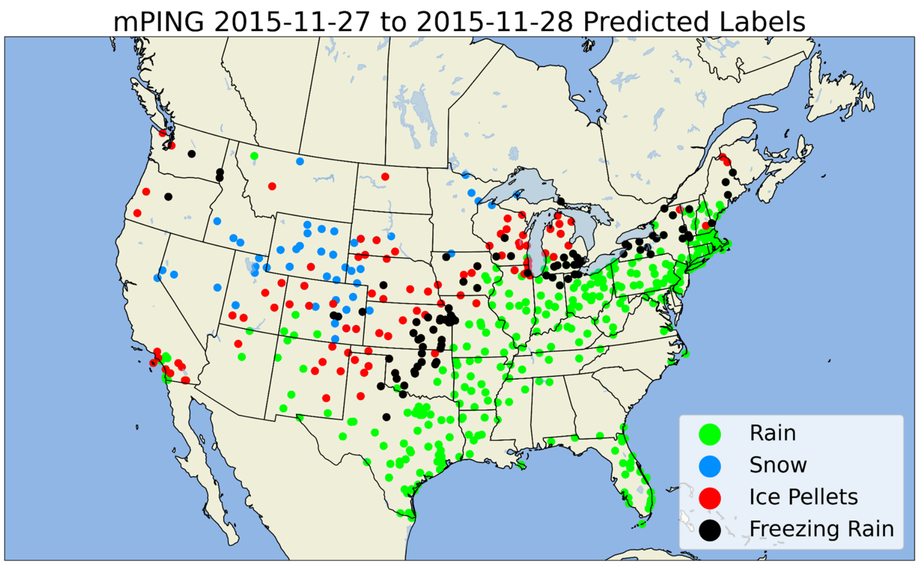


- Rain, snow, and freezing rain again had similar patterns to the overall diagram
- Ice pellets again become extremely overconfident at high confidences
- This trend could be caused by incorrect labels in the mPING dataset
- Burg et al. demonstrated that RAP underforcasts ice pellets compared to observations

mPING Case Study: True Labels vs. Predicted Labels



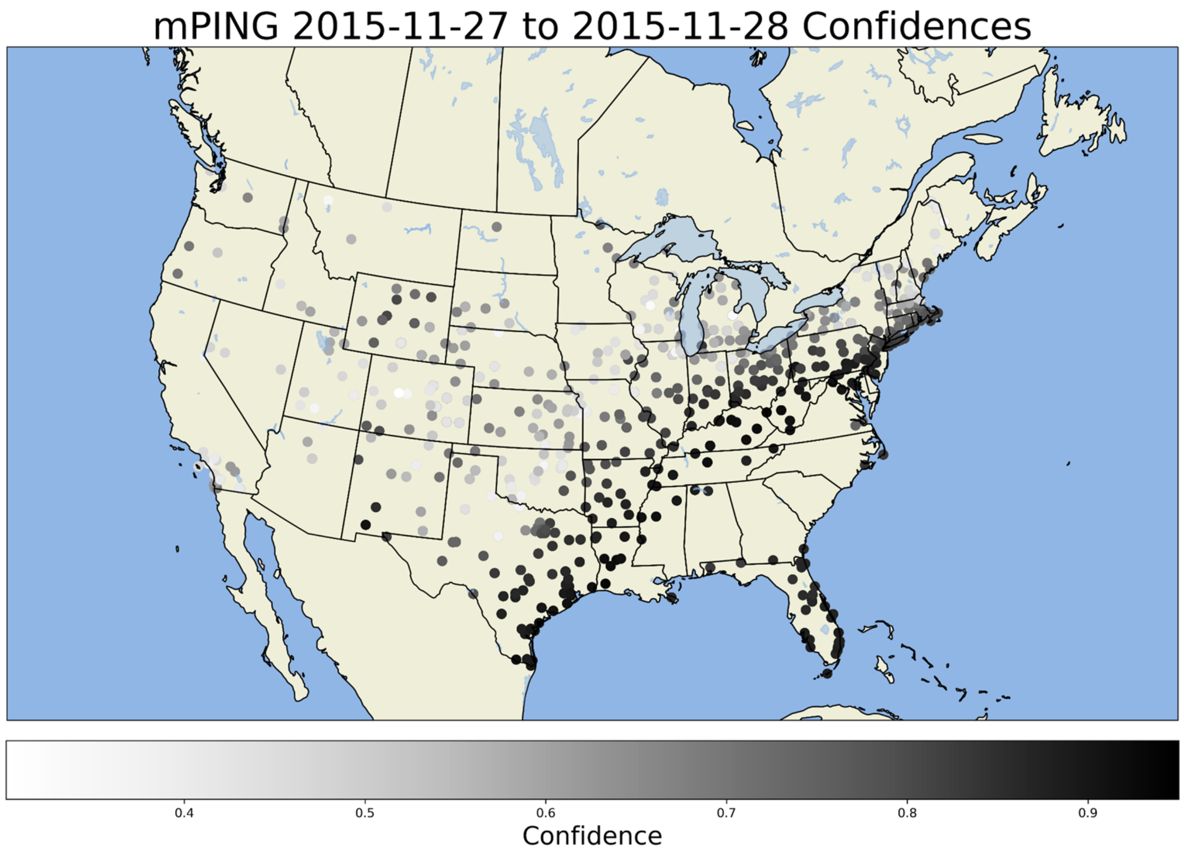
True Labels



Predicted Labels

- The mPING model got the spatial distribution of the ptypes roughly correct
- There is an overprediction of ice pellets and freezing rain at the expense of rain and snow in this case
- The ASOS model had similar results

mPING Case Study: Confidences



- The least confident predictions tend to be where freezing rain, ice pellets, or snow occurred
- In the ASOS model, the least confident predictions occurred in areas of freezing rain and ice pellets

Conclusions/Future Work

Conclusions

- Both models captured spatial distributions well, especially for rain and snow
- Both models were unable to predict ice pellets
- The ASOS model was more calibrated than the mPING model, with the exception of ice pellets

Future Work

- Continue model development and hyperparameter optimization on a neural network that can predict its own evidential uncertainty
- Explore other model structures such as a convolutional neural network

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References

Elmore, Kimberly & Grams, Heather & Apps, Deanna & Reeves, Heather. (2015). Verifying Forecast Precipitation Type with mPING. *Weather and Forecasting*. 30. 150313123347003. 10.1175/WAF-D-14-00068.1.

Burg, Tomer, Kimberly Elmore, & Heather Grams. (2017). Assessing the Skill of Updated Precipitation Type Diagnostics for the Rapid Refresh with mPING. Weather and Forecasting. 32. http://dx.doi.org/10.1175/ WAF-D-16-0132.s1.

https://github.com/NCAR/echo-opt