Developing a Machine Learning-Based Hail Climatology using the SHAVE and MYRORSS Databases

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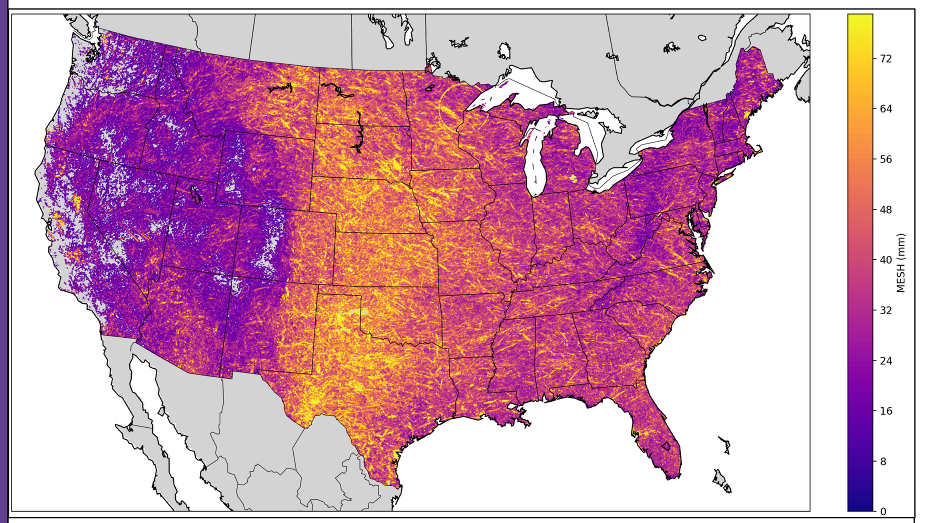
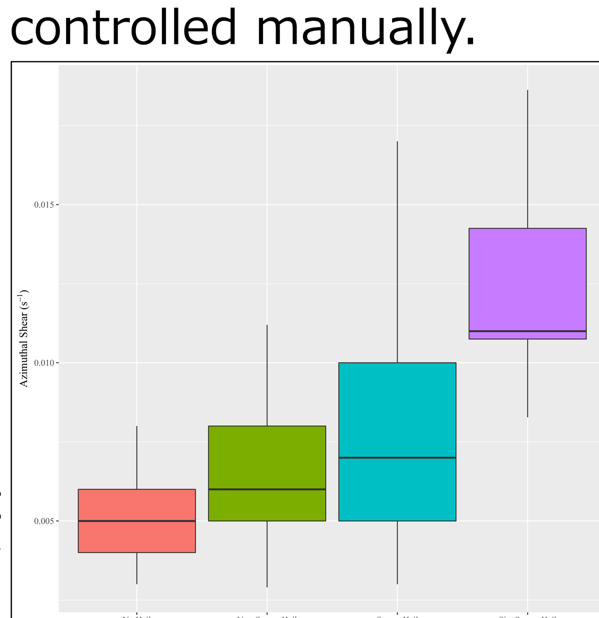
BACKGROUND

Previous hail climatologies have been created using hail reports collected by the National Weather Service which contain inaccuracies in reporting location and hail diameters, as well as lack of coverage in low population areas. The Multi-Year Reanalysis of Remotely Sensed Storms (MYRORSS) is a dataset for 1998-2011 using the Multi-Radar Multi-Sensor (MRMS) framework to merge the WSR-88D level-II data across the CONUS. This has allowed for more complete climatologies to be generated. This large dataset contains a 3-D reflectivity volume over the CONUS as well as derived products including Maximum Expected Size of Hail (MESH). MYRORSS is processed on a distributed computing system. Each year of processed data consumes 5T in storage and is quality controlled manually.



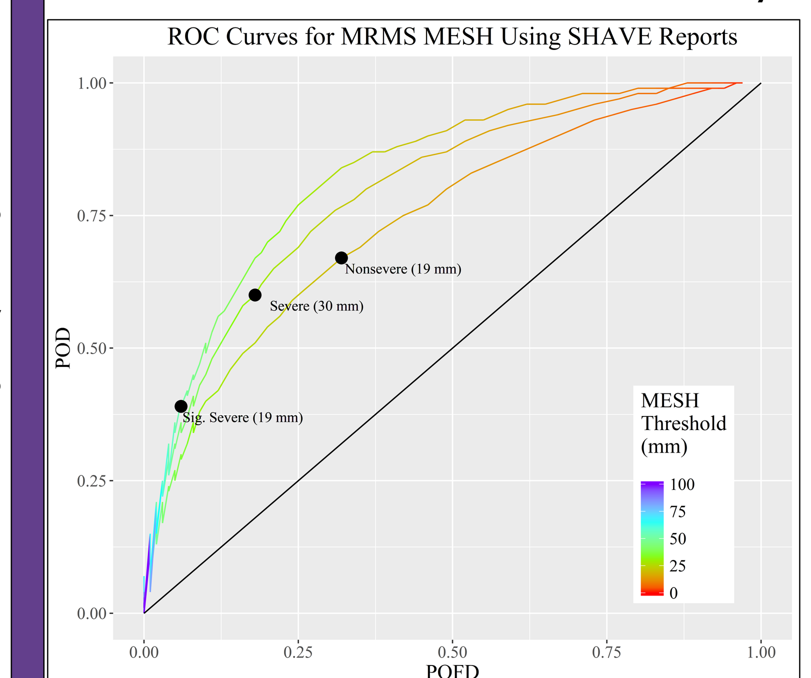
Above: 1998 – 2011 Maximal Accumulated MESH from the MYRORSS dataset.

Recent research (Ortega 2018) has shown the importance of maximal mid-level azimuthal shear for the maximum hail size along a storm's path to discern the differences between non-significant severe and significant severe hail (right). This shows that hail climatolgies cannot be generated without considering velocity derivatives.

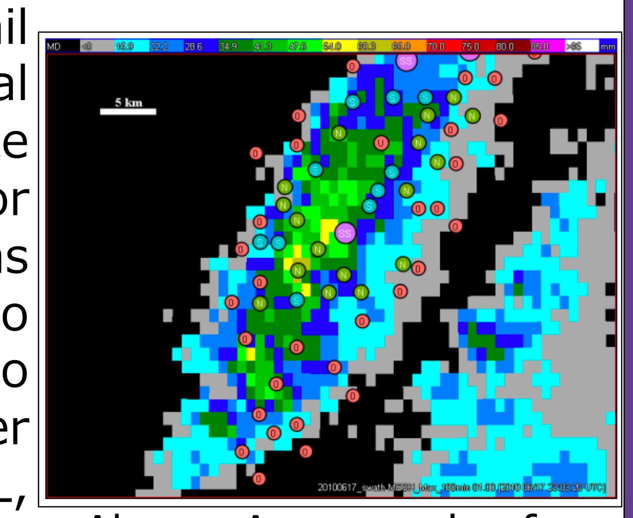


DATA

In Ortega (2018), MESH was compared to hail reports collected from the Severe Hazards Analysis and Verification Experiment (SHAVE) which showed room for improvement in hail prediction (left). The SHAVE dataset is a similar, but smaller dataset to MYRORSS but for individual storms rather than entire CONUS. This study uses this smaller separate data set, SHAVE, to develop methods using machine learning techniques to then apply to the much larger, CONUS-wide MYRORSS dataset.



Using the 735 cases of high density hail reports from the SHAVE data set, neural networks were trained to predict hail size diameters and classify hail categories. For each SHAVE cases, nearby radar data was processed through the MRMS framework to create a 3D reflectivity volume similar to that in the MYRORSS dataset. Other derived products, such as SHI and VIL, were combined with the azimuthal shear and reflectivity to be used within the neural networks.



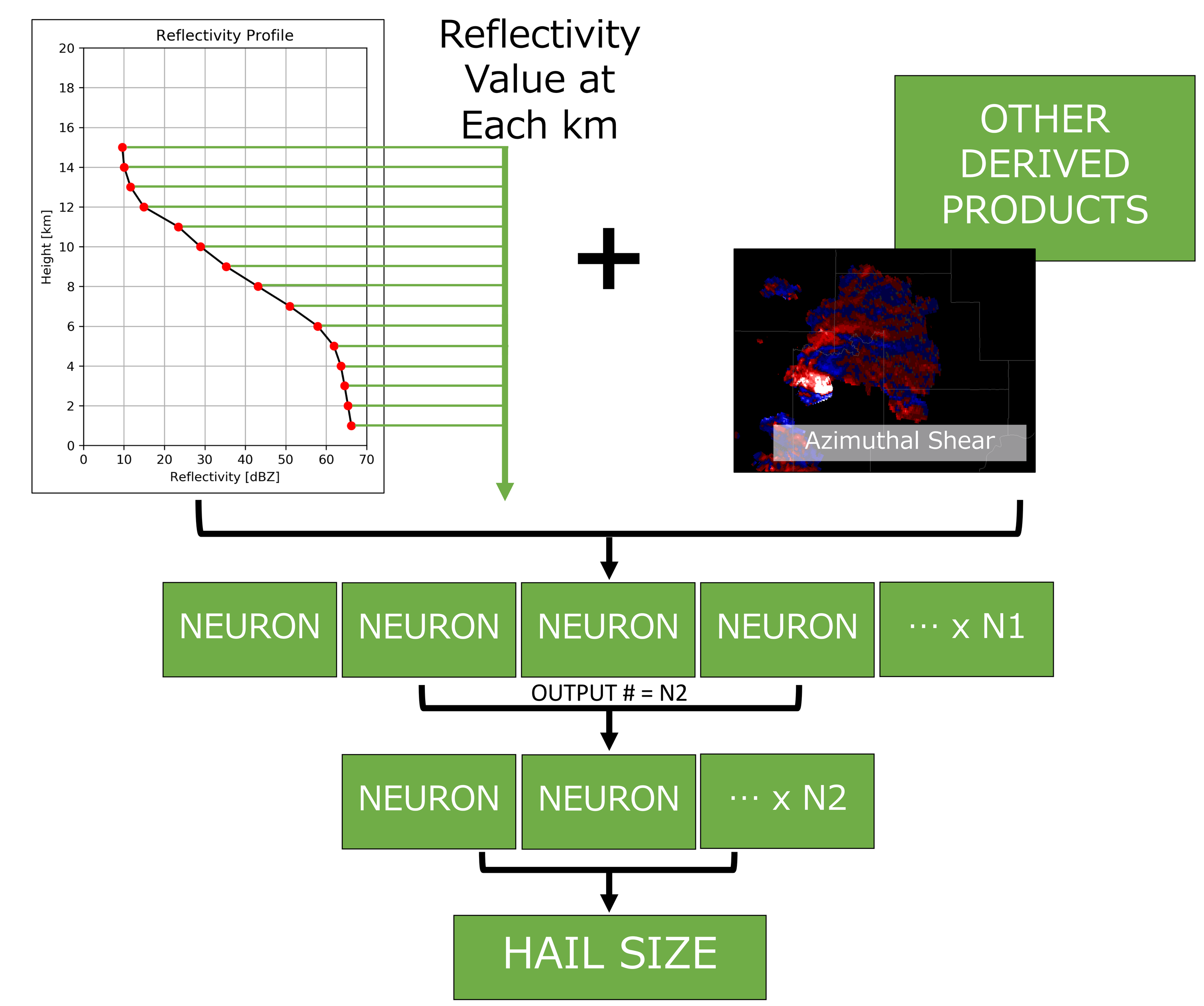
Above: An example of a SHAVE swath of hail reports overlaid on MESH.

METHODS

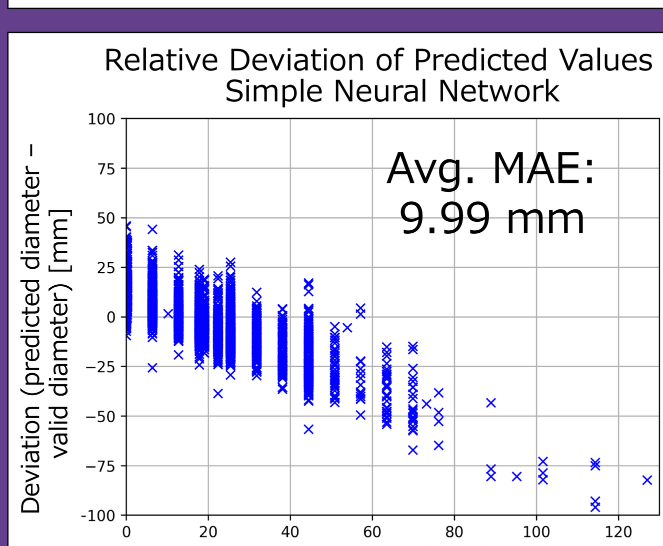
From the MRMS radar data, reflectivity profiles at specific heights and temperatures are created for each hail report and combined with the derived products and the azimuthal shear to be used as inputs to the neural networks.

Several different techniques within machine learning were applied to the neural networks which include: k-fold cross validation, adding skip-layers, changing the depth and width of the network, and changing the optimizers. In addition to the neural network, a gradient boosted decision tree was created to compare to the accuracy of the networks.

Example of simple neural network.

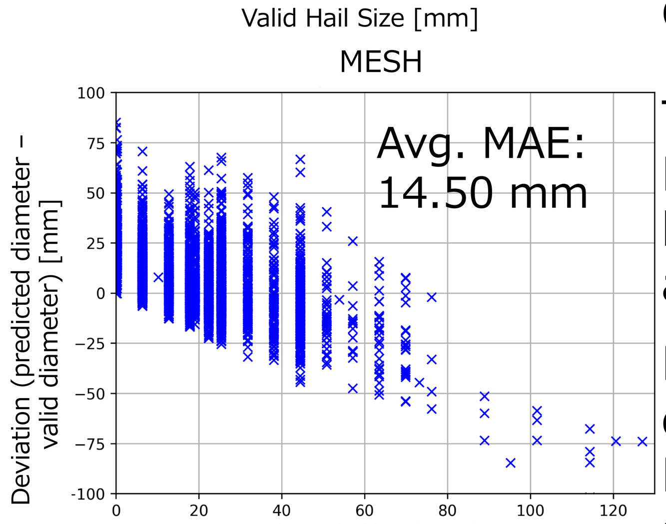


RESULTS



Ex1: Simple Fully-Connected Neural Network with 'RMSPROP' optimizer.

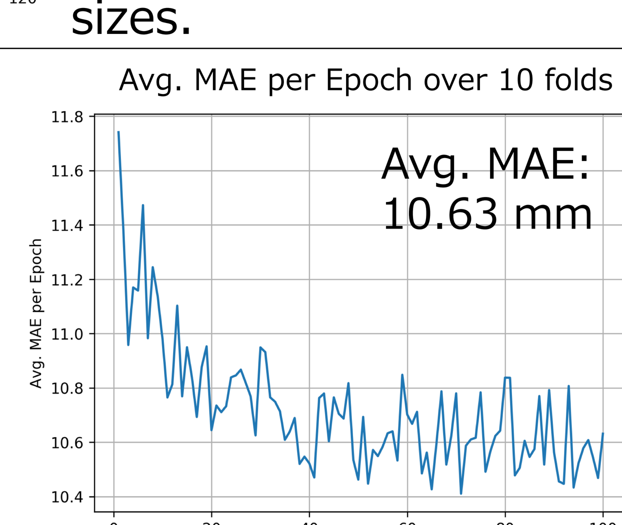
Neural network predicts hail sizes better than operational MESH.



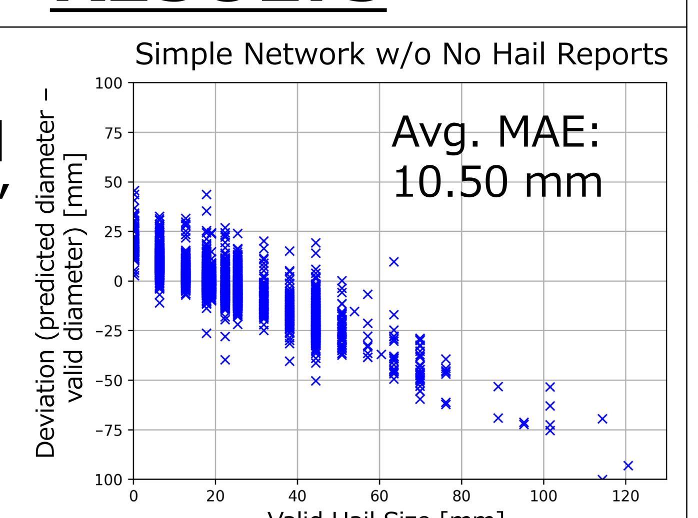
Top Left: Deviation of predicted hail diameters from actual hail sizes.

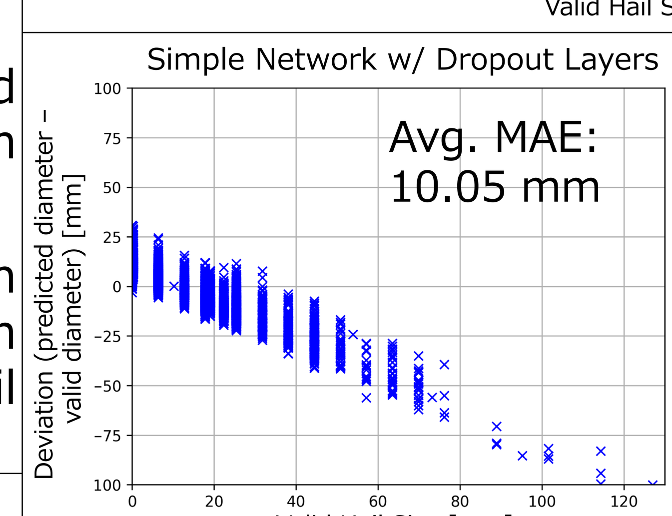
Bottom Left: Deviation of predicted sizes from MESH from actual hail sizes.

Ex2: K-fold Cross-validation with 10 folds does not perform as well as a simple network when comparing Avg. MAE's.



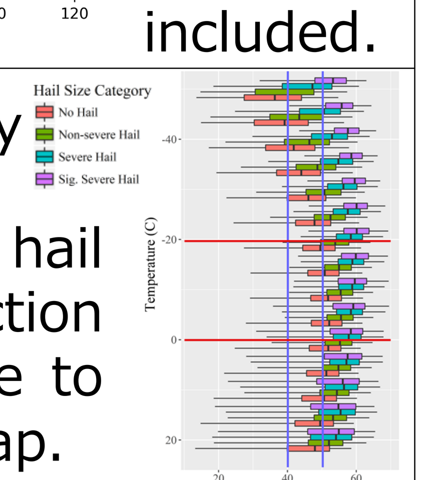
Ex3: Removed 'no hail' reports with similar results.

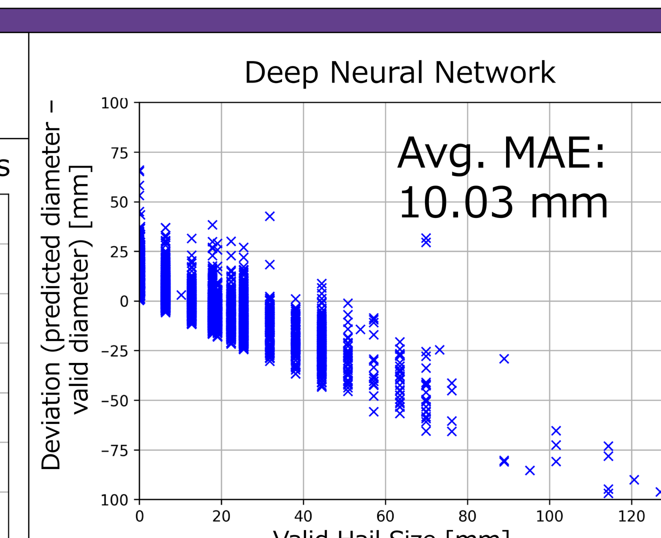




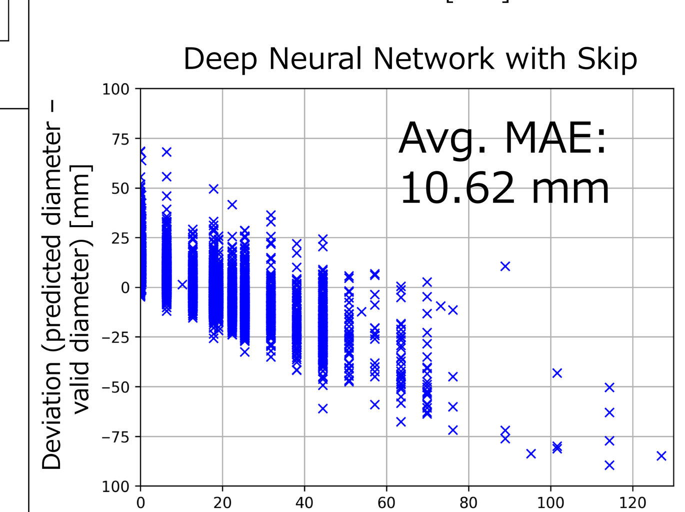
Ex4: Same Simple Network with Dropout Layers included.

Ex5: Hail Category Classification not nearly as good as hail diameter prediction which could be due to characteristic overlap.



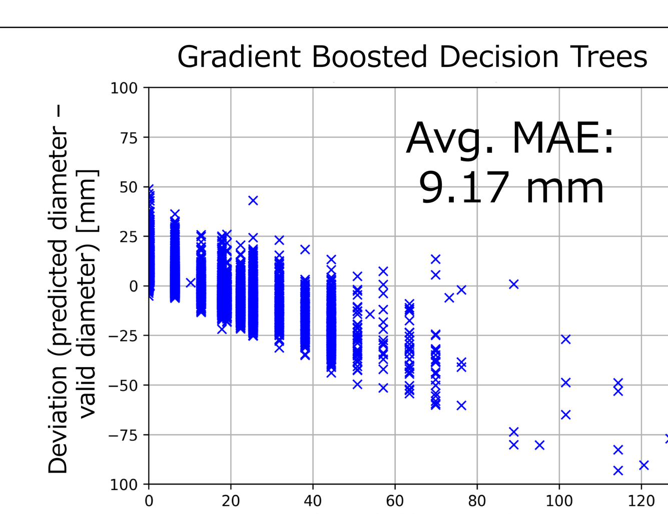


Ex6: Deep Neural Network (7 layers) compared to the simple network (3 layers) performs well but still not better than the simple network (top left).



Ex7: Same deep neural network with a skip input the initial data into the last layer as well (bottom left).

Ex8: Gradient Boosted Trees are another type of machine learning technique with a depth of 8 layers and 276 decision trees.



IMPLEMENTATION AND FUTURE WORK

- How do we take this methodology developed on this pixel to pixel basis and apply it on the much larger CONUS scale of 7000 pixels x 3500 pixels?
- Develop a convolutional neural network using the SHAVE data
  - Again, how to apply to the MYRORSS dataset?
  - In need of automated swatch identification
- How do we take these findings to then implement in real-time?

ACKNOWLEDGEMENTS

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