Random Forest Method for Hailstorm Nowcasting in the American Midwest

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Introduction

- The hyperlocal and abrupt nature of hail makes it challenging to produce accurate and advanced predictions on hail threat area and size of the hail.
- Evidence of large hail (≥ 1") is a sufficient condition for the issuance[1] of a **Severe Thunderstorm Warning**.
- While nearly all severe thunderstorms produce hail aloft, whether the hailstones can reach the ground depend on several factors[2]:
  - Strong updraft to keep hailstones aloft long enough
  - Deep vertical shear to separate the down/updrafts
  - High liquid water content to enhance hail growth
  - Low freezing level to minimize melting of hail, etc.
- Current approach to hail nowcasting relies on **radars** to detect imminent signs of hail (≥ 60 dBZ reflectivity and/or hail spike), paired with a knowledge of current atmospheric conditions via observations and **models**.
- Several recent studies[3,4] demonstrated high accuracy (≥ 91%) in hail nowcasting using **Random Forest (RF)**, a white-box ensemble supervised learning method.

Objective

Improve the existing hail warning system by developing an RF-based hail nowcasting model with real-time radar data combined with model reanalysis data as its inputs. Generate outputs as the probability of hail occurrence and maximum estimated hail size for the next 0–2 hours.

Data

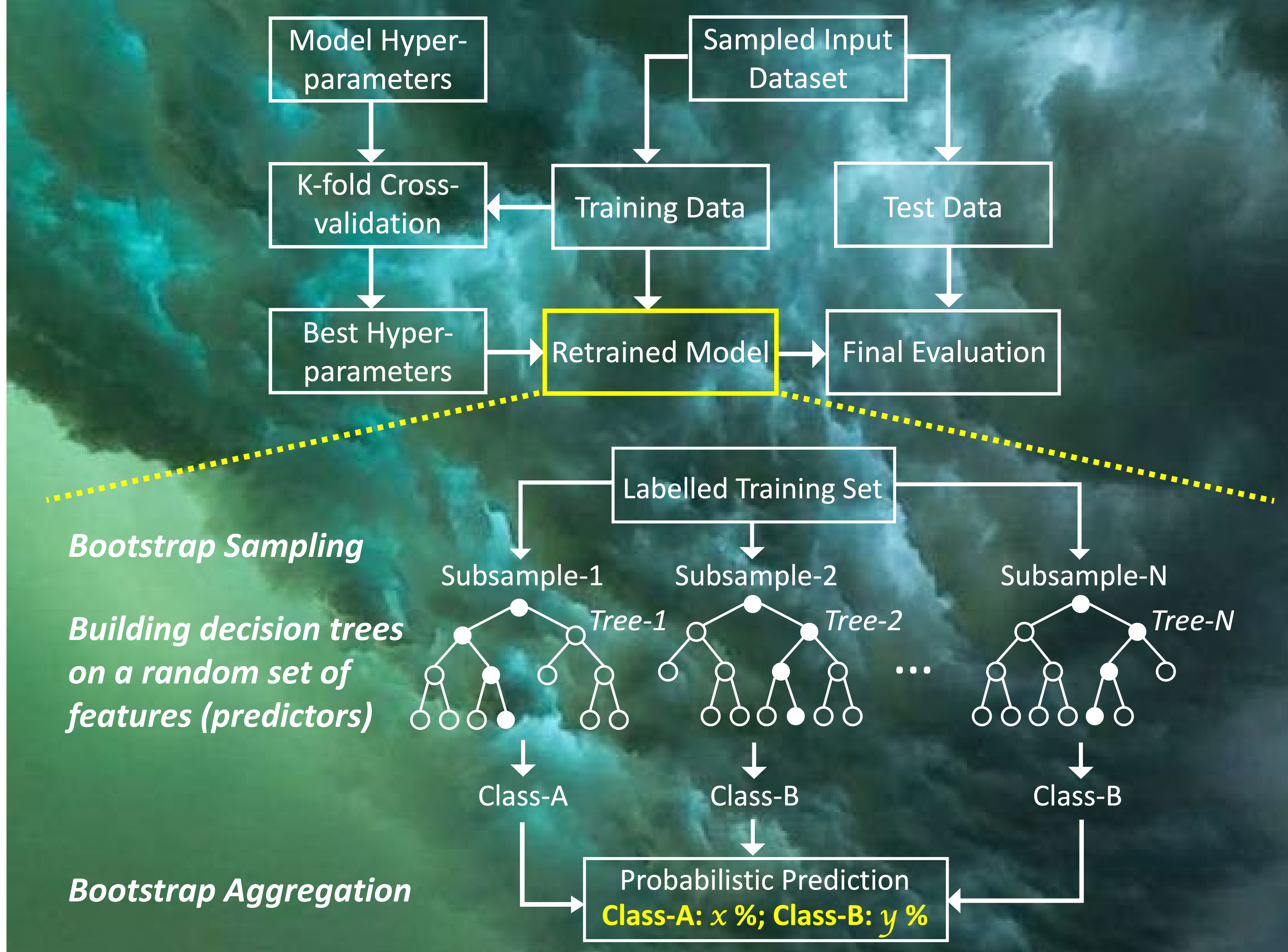
Data Type	Name (Source)	Lat/Lon Res.	Time Res.
Radar	MYRORSS (OU)	0.01° x 0.01°	5-min
Reanalysis	ERA5 (ECMWF)	0.25° x 0.25°	1-hr
Hail Report (nearest ¼")	Storm Event Database (SPC)	nearest 0.01°	nearest 5-min

- **Period of study**: 12:00 – 00:00 CST on all deep convective days from May to August 1999 – 2003
- **Domain of interest**: 39°N – 49°N, 85°W – 105°W (≃ 1100 km x 1600 km or 1.78M km^2 in area)
- **Deep Convective Day**: ≥ 10 hail, wind or tornado reports within the domain of interest on a given day

We achieved **95% accuracy** in forecasting hail activities up to **30 minutes** ahead.*

With improvements to our ensemble learning model, you could be even better prepared…

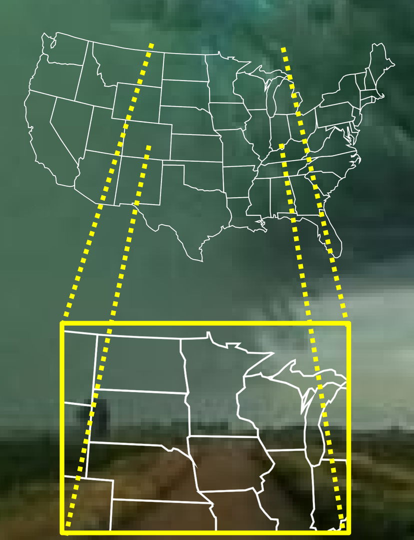
Random Forest Classifier for Hail Nowcasting



*(*Below: Preliminary results for 15-min and 60-min forecasts of 4 hail size categories)*

Feature Importance, 15-min

Top predictors	Score
Reflectivity at -20°C (20-km block)	0.182
VIL (20-km block)	0.163
Max. estimated size hail (20-km)	0.157
Bulk Richardson Number	0.106
Severe Weather Threat Index	0.081



Feature Importance, 60-min

Top predictors	Score
VIL (40-km block)	0.153
Reflectivity at -20°C (40-km block)	0.149
Bulk Richardson Number	0.139
Severe Weather Threat Index	0.135
Lowest reflectivity (40-km block)	0.081

Predictor importance vastly changes as prediction time increases → Value of multiple machines for multiple lead times

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Poster originally prepared for the CMOS-SCMO Congress 2023

Methodology

1. Select a set of **hail predictors** (35 in total) based on their relevancy to hail nowcasting from literature.
2. Calculate the hail predictors for all gridded data from all Deep Convective Days (240 days in total).
3. Split the above dataset by their **Maximum Estimated Size of Hail (MESH)** into four classes (*D < 1 mm, 1–5 mm, 5–20 mm and > 20 mm*). Randomly sample each class to extract a maximized balanced mix of hail case samples from the four classes.
4. Split the samples above into the **Training Set** & **Test Set** for the RF model, with MESH at the forecast validation time as the case label. Apply **k-fold cross-validation** to optimize the hyper-parameters.
5. Train the RF model. Evaluate its performance on the Test Set. Identify the top predictors for MESH at four forecast times *(T = 15, 30, 60 and 120-min)*.

Preliminary Results

Stage 3: All Data
Case I: T = 15 min

True Labels Ratio = 1:1:1:1 (Sample Size: 2,567,024)

Real Label \ Predicted Label	D < 1mm	1–5 mm	5–20 mm	≥ 20 mm	
D < 1mm	24.32%	0.76%	0.10%	0.04%	→ Category Size: 641,756
1–5 mm	0.52%	23.11%	0.42%	0.17%	→ Category Size: 641,756
5–20 mm	0.12%	0.54%	23.52%	0.89%	→ Category Size: 641,756
≥ 20 mm	0.01%	0.19%	0.53%	24.76%	→ Category Size: 641,756

Label Category	D < 1 mm	1 – 5 mm	5 – 20 mm	≥ 20 mm
Proportion Correct (PC)	98.45%	97.40%	97.40%	96.56%
Probability of Detection (POD)	96.43%	95.42%	93.82%	97.14%
False Alarm Ratio (FAR)	3.57%	4.58%	6.18%	2.86%
False Alarm Rate (F)	0.90%	2.04%	1.45%	1.52%
Critical Success Index (CSI)	94.01%	89.89%	90.05%	93.12%
Equitable Threat Score (ETS)	92.08%	86.84%	86.97%	87.11%
Heidke Skill Score (HSS)	95.88%	92.95%	93.03%	93.11%
Overall Accuracy	95.71%			

15-min forecasts

Stage 3: All Data
Case II: T = 60 min

True Labels Ratio = 1:1:1:1 (Sample Size: 2,377,064)

Real Label \ Predicted Label	D < 1mm	1–5 mm	5–20 mm	≥ 20 mm	
D < 1mm	23.07%	1.21%	0.28%	0.12%	→ Category Size: 594,266
1–5 mm	1.38%	22.13%	0.97%	0.76%	→ Category Size: 594,266
5–20 mm	0.80%	0.95%	22.54%	1.51%	→ Category Size: 594,266
≥ 20 mm	0.07%	0.14%	1.14%	24.76%	→ Category Size: 594,266

Label Category	D < 1 mm	1 – 5 mm	5 – 20 mm	≥ 20 mm
Proportion Correct (PC)	96.14%	94.59%	94.35%	92.99%
Probability of Detection (POD)	93.48%	87.68%	87.36%	94.44%
False Alarm Ratio (FAR)	6.52%	12.32%	12.64%	5.56%
False Alarm Rate (F)	3.06%	3.12%	3.24%	3.24%
Critical Success Index (CSI)	85.67%	80.36%	79.96%	85.98%
Equitable Threat Score (ETS)	81.34%	74.69%	74.03%	75.30%
Heidke Skill Score (HSS)	89.71%	85.51%	85.08%	85.91%
Overall Accuracy	90.67%			

60-min forecasts

- *Preliminary results were obtained from a one-year dataset (~2.5M samples)
- Overall, the RF performs better with no hail or with large hail and at shorter forecast times.
- As lead time increases, model and larger-scale radar inputs are more useful than higher-res radar fields
- **Probabilistic predictions** will replace this deterministic product in the next iteration.

References

[1] *Hail forecasting*. NOAA National Severe Storms Laboratory. (n.d.). https://www.nssl.noaa.gov/education/svrwx101/hail/forecasting/
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[4] Yao, H., Li, X., Pang, H., Sheng, L., & Wang, W. (2020). Application of random forest algorithm in hail forecasting over Shandong Peninsula. *Atmospheric Research*, *244*, 105093. https://doi.org/10.1016/j.atmosres.2020.105093