Detection of Hail Storms in Radar Imagery using Deep Learning

Melinda Pullman[1], Iksha Gurung[1], Rahul Ramachandran[2], and Manil Maskey[2]

[1]University of Alabama in Huntsville, Huntsville, AL, [2]NASA Marshall Space Flight Center, Huntsville AL

In 2016, hail was responsible for 3.5 billion and 23 million dollars in damage to property and crops, respectively, making it the second costliest weather phenomenon in the United States. In an effort to improve hail-prediction techniques and reduce the societal impacts associated with hail storms, we propose a deep learning technique that leverages radar imagery for automatic detection of hail storms. The technique is applied to radar imagery from 2011 to 2016 for the contiguous United States and achieved a precision of 0.848.

Introduction

Hail storms are primarily detected through the visual interpretation of radar imagery (Mroz et al., 2017). With radars providing data every two minutes, the detection of hail storms has become a big data task. As a result, scientists have turned to neural networks that employ computer vision to identify hail-bearing storms (Marzban et al., 2001). **In this study, we propose a deep Convolutional Neural Network (ConvNet) to understand the spatial features and patterns of radar echoes for detecting hailstorms.**

Data Pre-Processing

Download radar images for hailstorm reports → Crop radar images to 150x150 pixels with center of cropped image corresponding to location of hail report → Remove duplicate images → Split dataset into training, validation, and test sets (7:2:1)

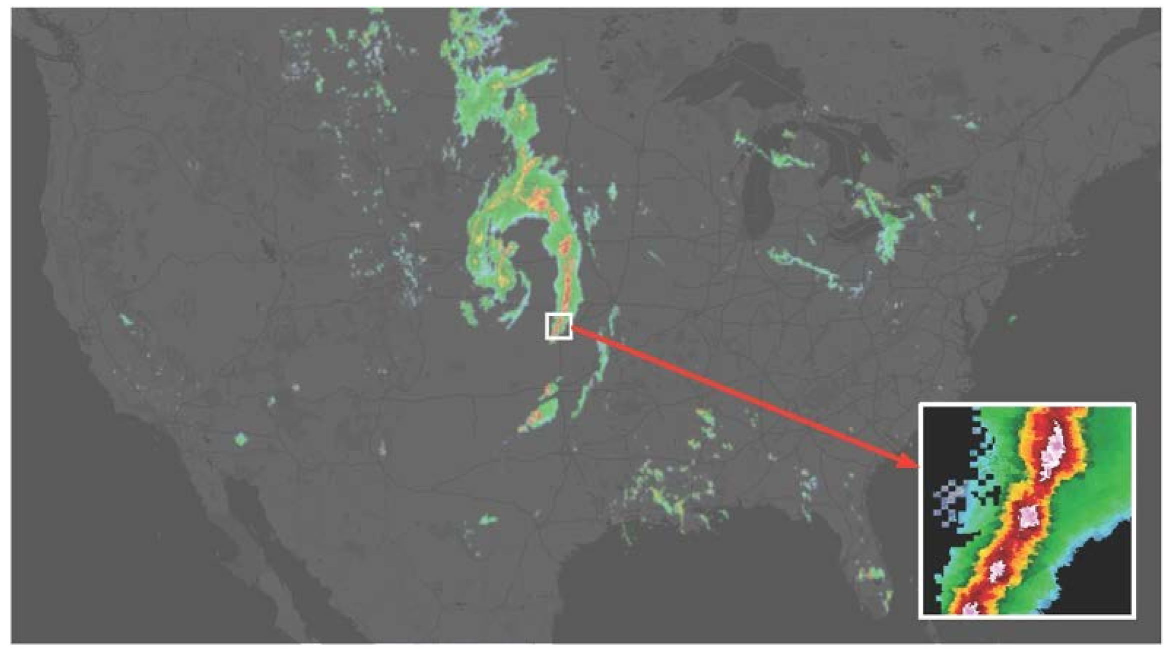
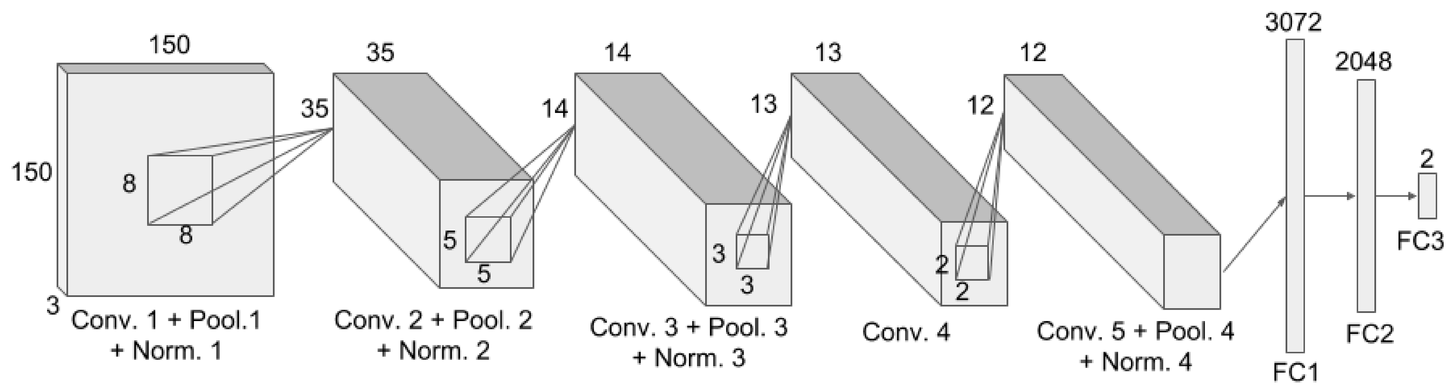


Figure 1: A national composite of NEXRAD base reflectivity image with a cropped subset corresponding to a hail report.

Ground Truth Labels	Training	Validation	Testing	Total
Hail	38,813	12,486	6,313	57,612
No Hail	54,580	14,199	7,030	75,809
Total	98,393	26,685	13,343	133,421

Table 1: The sizes of the image subsets for training, validation, and testing.

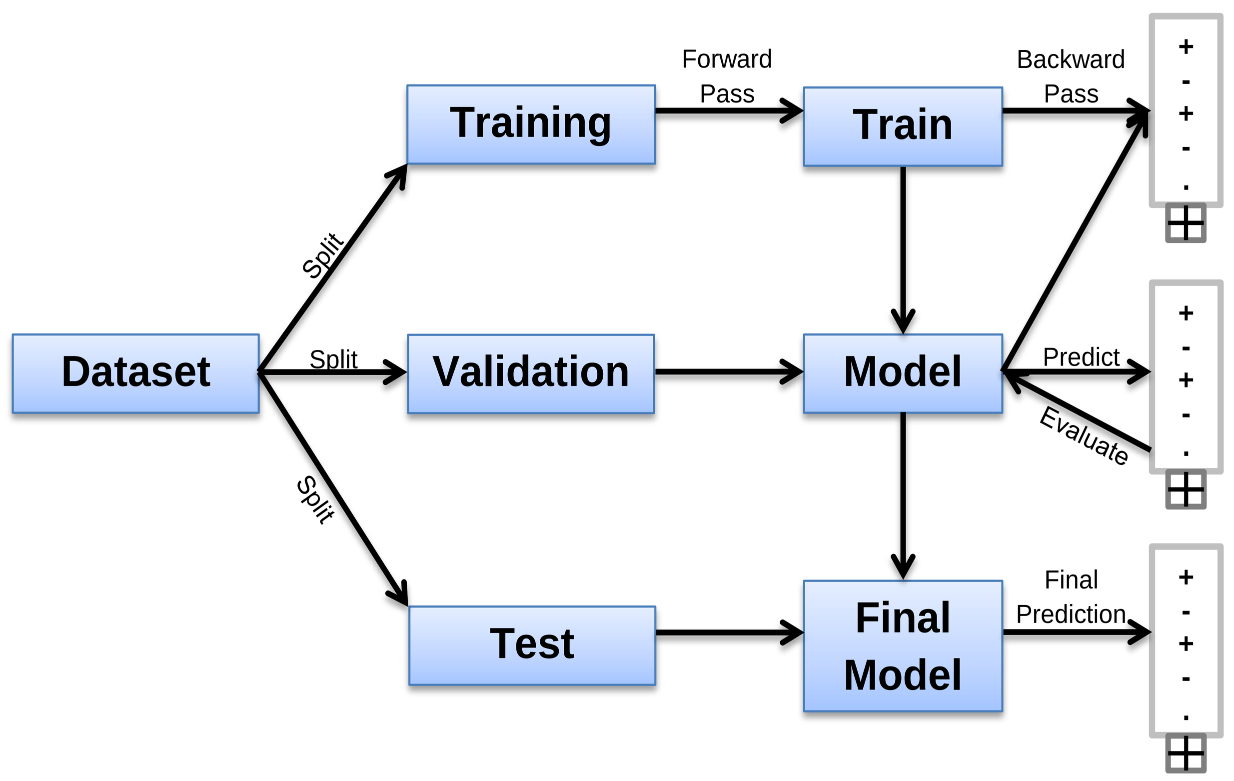
ConvNet



- **5 convolutional layers –**filtering for feature extraction. Non-linearities are introduced at the end of a convolutional layer
- ***4 pooling layers* –** reduces size of feature maps
- ***4 normalization layers* –** reduces model overfitting
- ***3 fully connected layers* –** computes class scores

Experimental Design

The 3 Experimental Phases of Deep Learning



Training:

- Forward pass – image is passed through network and predicted scores and losses are calculated
- Backward pass – weights are updated until loss is minimized

Validation:

- Check progress of learning
- Tune hyperparameters for better training

Testing:

- Unseen imagery is used to test accuracy of network

Learned Features and Spatial Patterns

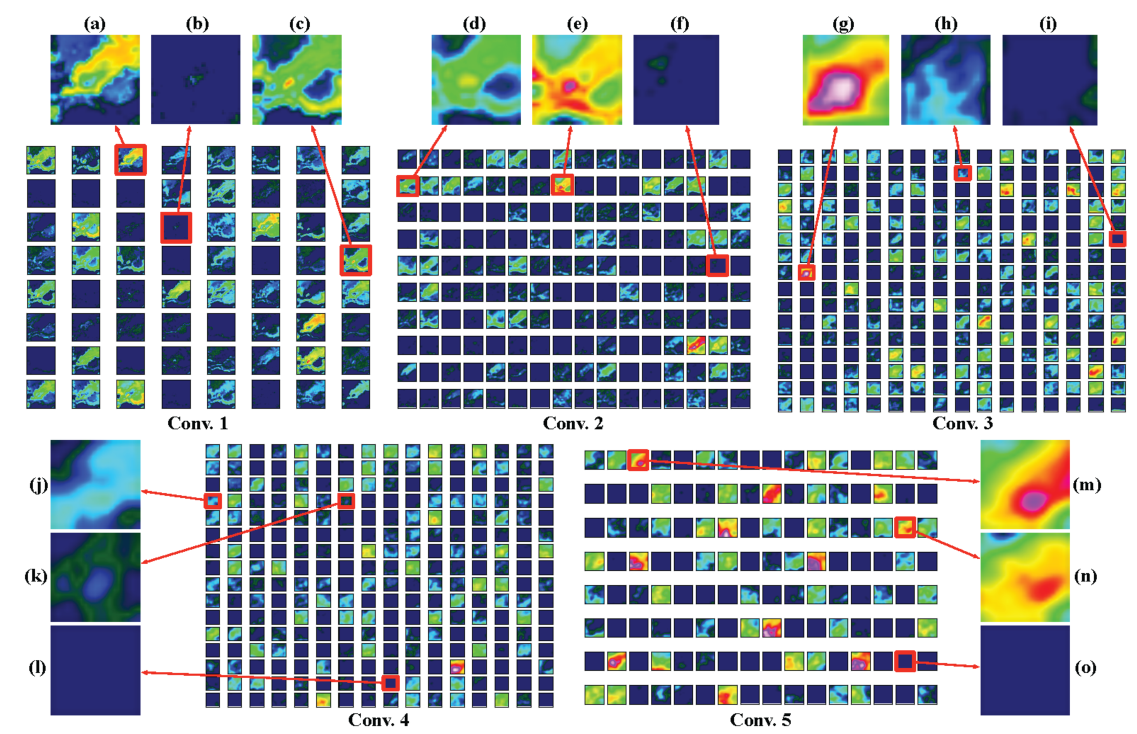


Figure 4: Features maps from each of the five convolutional layers show features the ConvNet is learning. Activated neurons in early layers appear more dispersed, and become more compact in later layers. From Figure 4 (a, c, d, e, g, m, and n), the network is learning the hail core, or cluster of higher reflectivities associated with hail.

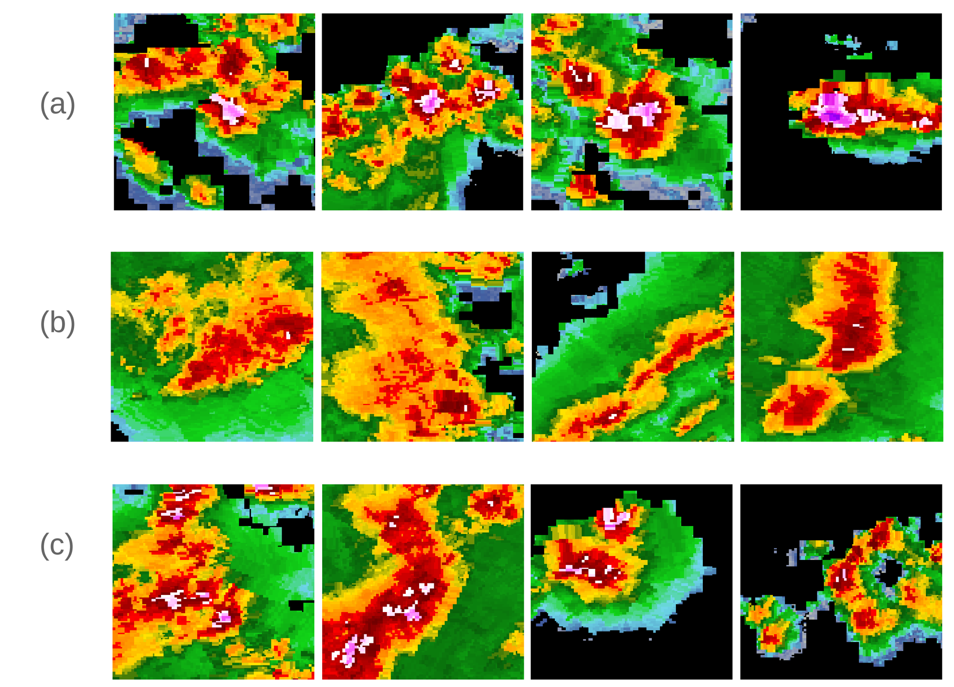


Figure 5: Example test images classified from our trained ConvNet. (a) test hail images correctly classified as hail, (b) test hail images incorrectly classified as no hail, and (c) test no hail images incorrectly classified as hail. The trained ConvNet relies upon the presence of higher reflectivities (>60dBZ) to classify images.

Results

	Predicted Hail	Predicted No Hail	Total
Actual Hail	4,903 (TP)	1,410 (FN)	6,313
Actual No Hail	883 (FP)	6,147 (TN)	7,030
Total	5,786	7,557	13,343

Table 2: The confusion matrix for "Hail" (positive) and "No Hail" (negative) classification.

Approaches			Precision	POD	FAR	CSI
Ours			0.847	0.777	0.153	0.681
SVM (with Scikit-learn package)			0.779	0.782	0.160	0.640
Auer, 1994	A regression model	without cloud-top temperature parameter	—	0.560	0.220	0.480
		with cloud-top temperature parameter	—	0.910	0.120	0.810
Bauer-Messmer and Waldvogel, 1997	VIS clusters		—	1.000	0.810	˜0.000*
	Three-step area threshold		—	0.840	0.660	0.319*
	Infrared threshold		—	0.560	0.470	0.374*
Zibert and Zibert, 2013	A min & max pixel detection algorithm		0.540	0.660	—	—
Merino et al., 2014	CM & HM algorithms		—	0.769	0.167	0.667*
Ferraro et al., 2015	BT thresholding		—	0.400	0.700	0.207*
Mroz et al., 2017	Ku-based parameter threshold		—	0.653	0.410	0.449
Ni et al., 2017	Threshold with hail detection criteria		—	0.450	0.240	0.394*

Table 3: Comparison of our ConvNet performance with the existing approaches for hailstorm detection. CSI scores, marked with asterisks, are computed with paper-provided POD and FAR values.

Conclusion and Future Work

We developed a model capable of automating the process of hailstorm detection. Because satellite imagery can provide data across a larger, continuous spatial domain compared to radar imagery, it would be more advantageous to develop a ConvNet capable of detecting hailstorms from satellite imagery.

Future work includes:

- applying the ConvNet from this study to satellite imagery for hail detection
- incorporating data from numerical weather prediction models for enhanced accuracy.

References

1. Maraban et al. (2001), "A Bayesian Neural Network for Severe-Hail Size Prediction," *Weather and Forecasting, 16,* 600-610.
2. Mroz et al. (2017), "Hail-Detection Algorithm for the GPM Core Observatory Satellite Sensors," *Journal of Applied Meteorology and Climatology, 56*, 1939-1957.

Contact: mkp0015@uah.edu

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THE UNIVERSITY OF ALABAMA IN HUNTSVILLE