Detection of Hail Storms in Radar Imagery using Deep Learning

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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

Split dataset into training, validation, and test sets (7:2:1)

Remove duplicate images

Download the dataset

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

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

<table>
<thead>
<tr>
<th></th>
<th>Training</th>
<th>Validation</th>
<th>Testing</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hail</td>
<td>33,480</td>
<td>5,458</td>
<td>2,000</td>
<td>41,038</td>
</tr>
<tr>
<td>No Hail</td>
<td>6,623</td>
<td>1,088</td>
<td>400</td>
<td>8,131</td>
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<tr>
<td>Total</td>
<td>40,103</td>
<td>6,546</td>
<td>2,400</td>
<td>51,459</td>
</tr>
</tbody>
</table>

ConvNet

The 3 Experimental Phases of Deep Learning

Dataset

Training

Validation

Model

Test

Final Prediction

Final Prediction

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

Experimental Design

The 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

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 4,003 (TP) 1,410 (FN) 5,413

Actual No Hail 883 (FP) 6,147 (TN) 7,030

Total 5,886 7,557 13,343

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

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


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