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 approaches for 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.

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)

Experimental Design

The 3 Experimental Phases of Deep Learning

1. Training: Forward pass – image is passed through network and predicted scores and losses are calculated
2. Backward pass – weights are updated until loss is minimized
3. Validation: Check progress of learning
4. Testing: Unseen imagery is used to test accuracy of network

Learned Features and Spatial Patterns

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

Results

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

<table>
<thead>
<tr>
<th>Actual Class</th>
<th>Predicted Class</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hail</td>
<td>4,903 (TP)</td>
<td>6,313</td>
</tr>
<tr>
<td>No Hail</td>
<td>1,410 (FP)</td>
<td>7,030</td>
</tr>
<tr>
<td></td>
<td>5,813</td>
<td>13,343</td>
</tr>
</tbody>
</table>

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


Contact: mkp0015@uah.edu

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