



Automated Extraction of Weather Variables from Imagery

tech transfer summary

Machine learning techniques that automatically identify winter road surface conditions in highway camera images have the potential to improve maintenance decision support systems.

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RESEARCH PROJECT TITLE

Automated Extraction of Weather Variables from Imagery

SPONSOR

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The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

The opinions, findings, and conclusions expressed in this publication are those of the authors and not necessarily those of the project partners.

Background

Department of transportation (DOT) maintenance supervisors use tools such as maintenance decision support systems (MDSS) to monitor road surface conditions (RSC) during winter weather. MDSS automatically attempt to deduce current RSC based on road weather information system (RWIS) and other data.

Although current MDSS often include highway camera imagery, they typically do not incorporate automated image recognition to improve RSC assessments. Meanwhile, recent research has evaluated the use of machine learning (ML) techniques such as convolutional neural networks (CNN) to automatically identify winter RSC using highway camera images.

Problem Statement

Because the use of ML techniques for automated RSC identification has appeared to be quite successful, an opportunity exists to transition these techniques from the research community to the DOT community for implementation in MDSS and other tools.

Goal and Objectives

The overarching goal of this project was to identify ML approaches for the automatic identification of winter RSC that are sufficiently accurate to be useful to DOT maintenance staff and that can be implemented effectively in MDSS or standalone tools.



RWIS camera image showing snow on the shoulders and traces of snow in the lanes

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Specific objectives were as follows:

1. Determine which ML techniques—including both open-source and cloud-based proprietary techniques—best identify RSC from camera imagery and other relevant data
2. Identify ML approaches that can be implemented in MDSS or other tools
3. Determine how to implement the identified ML techniques within the context of an MDSS or standalone tools

Research Description

RWIS camera images from the North Dakota DOT (NDDOT) were collected from January through April and from October through December in 2022 and were archived using cloud storage. These images were supplemented with previously archived camera images from Alaska. RWIS sensor data and speed, volume, and occupancy (SVO) data were also collected from NDDOT.

The research team manually labeled approximately 20,000 images while considering issues such as the labeling criteria to use, how to handle edge cases, the effects of camera angle and visibility conditions on RSC identification, and the possible use of multiple snow categories. Given the set of images available, the research team focused on two categorizations: (1) “snow” versus “no snow” and (2) high visibility versus low to moderate visibility.

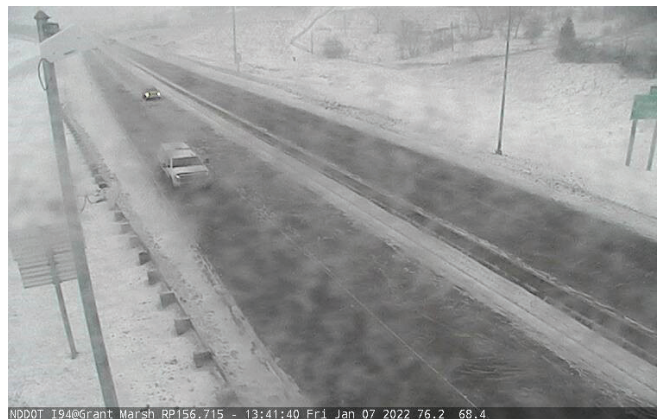
Three ML approaches were evaluated for RSC image identification: (1) open-source CNN algorithms, (2) Amazon Web Services (AWS) Rekognition, and (3) Microsoft Azure Custom Vision. The research team performed 11 single-camera and multiple-camera ML modeling experiments using images from I-29 at Grand Forks, North Dakota, and a bridge in Alaska.

Key Findings

- Establishing a set of clear, unambiguous, and consistent rules is important for RSC labeling.
- Using a time series of camera images at a single site is a quick, accurate, and effective way to label RSC.
- A clear view of the road in a camera image is important for accurate labeling and good ML performance. A dirty camera lens, glare, darkness, low visibility, high distance to the road, and obstructions all have a negative effect on the identification of RSC.
- For successful ML, it is important that an adequate number of accurately labeled images be available for each RSC category.
- Cloud vendor image classification technology exhibited similar performance to open-source image classification technology and was easier to use.
- Single-camera and multiple-camera ML models exhibited similar performance when tested using temporally segregated image data from the cameras included in the training set. Multiple-camera ML models exhibited poorer performance when evaluated using images from a site not included in the training set.
- ML classification technology performed extremely well in many of the experiments and shows promise for integration into MDSS and other tools.



RWIS camera image showing no snow and high visibility



RWIS camera image with a dirty camera lens resulting in low visibility



RWIS camera image showing low visibility and snow on the shoulders and traffic lanes

Implementation Readiness and Benefits

With the proper preparation, ML techniques can be used successfully to automatically identify winter RSC in highway camera images. Integrating these techniques into MDSS or other tools can result in a number of benefits:

1. Improved RSC assessments
2. Improved road treatment recommendations due to more accurate RSC identification
3. Improved compliance with MDSS recommendations due to user confidence

The following steps can be taken to incorporate automatic RSC identification into MDSS or other tools:

1. Select a set of high-priority camera sites where automatic image classification will have clear benefits, e.g., where snow is especially problematic or timely maintenance is required.
2. Archive camera images at the sites of interest for at least one complete winter season, though two or more winter seasons is preferable.
3. While archiving the camera images, perform regular and consistent spot checks to ensure that the images do not have critical quality problems.

4. Formulate image labeling rules that support clear, unambiguous, and consistent labeling by category, and take advantage of time series labeling to improve efficiency.
5. Test the performance of the labeling procedure using cloud-based image classification technology on training and test sets captured at single camera sites, refining the labeling procedure until the ML model performs adequately on the test sets.
6. Formulate combined training and test sets covering multiple camera sites, generate ML models for classification of RSC in images, and test the ML models on holdout images that are temporally or spatially separate from the training images.
7. Integrate the ML models into the target MDSS or other tools.

Additional work is needed to determine which RSC categories are most helpful for DOT maintenance personnel, how RSC image classification might help determine road friction, how additional RWIS or traffic data might improve image classification, and other areas.