working to advance road weather information systems technology

Roadway Ice/Snow Detection Using a Novel Infrared Thermography Technology

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Aurora Project 2020-02

Final Report
February 2024

About Aurora

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.

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16. Abstract

Safety is a principal concern for highway transportation, and slippery roads can pose high risks for vehicle crashes in snowy regions, which cover about 70% of road networks in the United States. Slippery road conditions can significantly increase the risk of vehicle crashes. Therefore, roadway agency staff find it critical to clear road surfaces in time to ensure traffic safety during ice and snow seasons. Moreover, the capability to estimate multi-lane roadway snow coverage is instrumental for snow plowing performance evaluation and resource planning for snowy regions during winter seasons.

The researchers developed and evaluated a sensing technology to evaluate multi-lane roadway snow coverage leveraging non-invasive dual-spectrum cameras, computer vision, and machine learning algorithms. The use of optical and infrared images for slippery roadway condition detection has the potential to operate in different illumination conditions.

The team deployed two dual-spectrum cameras, which can acquire both optical and infrared images of roadways. Computer vision algorithms were developed to perform image registration, segmentation, lane splitting, classification, and clustering.

Furthermore, to account for the relatively limited data volume, the researchers established a transfer learning framework, which greatly eliminated the need for training a large number of hyperparameters. The transfer learning algorithm achieved a precision of 88% using daytime optical images and an impressive precision of 94% when using nighttime thermal images, despite the constraints imposed by using a limited dataset.

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ROADWAY ICE/SNOW DETECTION USING A NOVEL INFRARED THERMOGRAPHY TECHNOLOGY

Final Report
February 2024

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EXECUTIVE SUMMARY

Safety is a principal concern for highway transportation, and slippery roads can pose high risks for vehicle crashes in snowy regions, which cover about 70% of road networks in the United States. Slippery road conditions can significantly increase the risk of vehicle crashes. Therefore, roadway agency staff find it critical to clear road surfaces in time to ensure traffic safety during ice and snow seasons. Moreover, the capability to estimate multi-lane roadway snow coverage is instrumental for snow plowing performance evaluation during winter seasons in snowy regions.

The goal of this project was to develop a convenient tool capable of multi-lane snow coverage estimation in winter seasons. The researchers developed a sensing technology to evaluate multi-lane roadway snow coverage leveraging non-contact dual-spectrum cameras, computer vision, and machine learning algorithms. The use of optical and infrared images for slippery roadway condition detection has the potential to operate in different illumination conditions.

The team adopted two dual-spectrum cameras, which can provide both optical and infrared images of roadways. Computer vision algorithms were developed to perform image registration, segmentation, lane splitting, classification, and clustering. To account for the relatively limited data volume, the team also established a transfer learning framework, which greatly eliminated the need for training a large number of hyperparameters. The transfer learning algorithm achieved a precision of 88% using daytime optical images and an impressive precision of 94% when using nighttime thermal images, despite the constraints imposed by using a limited dataset. The research involved the following three phases:

- Data collection over two winter seasons and pre-processing
- Development and evaluation of computer vision algorithms
- Development and evaluation of a transfer learning framework

The following key findings were identified based on the work conducted in this project.

- The developed data acquisition system and computer vision algorithms can be used for snow detection and roadway snow coverage estimation.
- With the specific data acquisition system, optical images are suitable for snow detection with sufficient illumination conditions, and infrared images outperform optical ones when illumination is low while temperature contrast is high.
- The utilization of the transfer learning model proves to be particularly advantageous with a relatively small amount of labeled optical and infrared image data.
- The efficacy of the U-Net transfer learning model generally demonstrated similar or superior performance when compared to that of the computer vision algorithms.

INTRODUCTION

Problem Statement/Need

Safety is a principal concern for highway transportation, and slippery roads can pose high risks for vehicle crashes in snowy regions, which cover about 70% of road networks in the United States. The Federal Highway Administration (FHWA) safety data report that 24% of weather-related vehicle crashes occur on snowy or icy roads, which result in an average of 1,300 deaths and 116,800 injuries per year (FHWA 2023). Slippery road conditions can significantly reduce tire friction and, along with low visibility conditions, lengthen vehicle braking distances, thereby increasing the risks of vehicle crashes.

Agency roadway staff find that it is critical to clear road surfaces in time to ensure traffic safety during ice and snow seasons. Consequently, winter traffic safety management has been viewed as the top priority of many state departments of transportation (DOTs) in snowy regions.

Development of technology that can assess slippery road conditions for real-time traffic safety evaluations is highly desirable. However, it remains a challenge because accurate and full-scale detection of ice and snow patterns on the pavement is difficult to achieve.

Background

To quantify winter weather severity and evaluate snow removal performance in snowy regions, state DOTs have been employing or investigating winter severity indices. Many DOTs indirectly track severity by calculating the extent to which their systems meet the level of service (LOS). On the other hand, many states evaluate the winter weather severity index by accounting for the atmospheric and/or road conditions.

Roadway snow detection for road safety has been extensively investigated, aiming to supply local agencies, drivers, or autonomous vehicles with real-time roadway weather information and facilitate their decision-making (Ruiz-Llata et al. 2014, Karsisto and Loven 2019, Eom et al. 2021). A wide range of sensing technologies have been deployed for real-time data collection, where the road surface temperature and slippery conditions are essential parameters to facilitate hazardous road condition detection and warning. Much effort has been invested on this front, as shown in Table 1.

Table 1. Preliminary summary of past work on roadway snow/ice detection

Item #	Phenomena/Technique	Investigators/Relevant publication
1	RWIS	Aurora 2005*
2	Infrared thermometer	Bridge 2008, Ye et al. 2011
3	Passive infrared thermography with radiation polarization	Reed and Barbour 1997
4	Active infrared radiation backscatter	Bridge 2008, Misener 1998, Joshi 2002
5	Video camera	Kwon 2002, Saito and Yamagato 2014*
6	Laser light polarization	Schmokel 2004
7	Microwave reflection	Kubichek and Yoakum-Stover 1998
8	Pavement temperature sensors	Adams 2005*, SRF Consulting Group Inc. 2015*

*Aurora reports

One popular solution is the road weather information system (RWIS) (Eriksson and Norrman 2001, Aurora 2005, Ewan et al. 2013, Kwon et al. 2017), which provides temperature, humidity, and precipitation data (Zang et al. 2019, Jonsson 2011). Another widely adopted option, remote road surface state sensors, allows measurements of road surface temperature and condition (Bridge 2008, Mercelis et al. 2020). However, both options only support single-spot measurement, which does not necessarily represent "true" road surface conditions of interest. Moreover, measurement accuracy and required calibration frequency become concerns for practical operation.

Despite intensive research efforts over the past 20 years, a need for sensing technology for road temperature and slippery condition detection persists.

Detailed Summary of Previous Research

Researchers have extensively adopted image processing and machine learning to analyze slippery roadway conditions and weather conditions based on optical images. With recent advancements in machine learning, supervised learning frameworks lend themselves to handling object recognition and image segmentation.

Zhao et al. (2017) classified road surfaces into five different types, i.e., dry, wet, snow, ice, and water. They established a road surface state database by involving nine-dimensional (9D) color eigenvectors as well as four texture eigenvectors and used a support vector machine (SVM) for roadway condition classification.

Qian et al. (2016) characterized the prior distribution of road pixel locations from training data and fused the normalized luminance and texture features with probability to classify road surface conditions.

To support snowy weather detection, Khan and Ahmed (2019) classified road weather into three categories (clear, light snow, and heavy snow) and developed a real-time in-vehicle snow detection system that supports trajectory-level weather detection. They evaluated the performance of SVM, k-nearest neighbor (K-NN), and random forest (RF) using the dataset from the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) video data.

Roser and Moosmann (2008) used SVM to classify inclement weather conditions (clear, light rain, and heavy rain) considering five image features, i.e., local contrast, minimum brightness, sharpness, hue, and saturation.

Another study developed convolutional neural networks (CNNs) to identify adverse weather conditions from a road camera, which could be implemented at the in-vehicle level (Dahmane et al. 2018).

Lei et al. (2020) introduced their snowy driving dataset to train and test models for pixel-wise semantic labeling.

When illumination or weather conditions are insufficient to support reliable optical image segmentation, infrared thermography provides an alternative measure for object detection, where the infrared image's pixel intensity represents temperature. Vachmanus et al. (2021) proposed a multi-modal fused red, green, blue-thermal (RGB-T) semantic segmentation using optical and infrared images as the inputs for their networks to study the semantic segmentation of roads in snowy weather, especially focusing on human subject detection in snowy environments.

Li et al. (2018) developed an algorithm to identify pedestrians through infrared image segmentation with the help of background likelihood and object-biased saliency.

Infrared image segmentation is also widely used for military purposes. Bai et al. (2016) successfully developed a feature-based fuzzy inference system to segment low-contrast infrared images containing ships.

Landry and Akhloufi (2022) contributed to this field by estimating snow coverage using surveillance cameras and proposing a powerful ensemble machine learning model combining CNN and SVM. The results of their study demonstrated superior accuracy compared to existing research.

Bhatia et al. (2022) approached the challenge of pothole detection by collecting a diverse dataset of thermal images under various weather conditions. Through data augmentation techniques and leveraging of a CNN model, they successfully identified potholes, addressing a critical aspect of roadway safety.

To address the limitations of traditional image recognition technology for road recognition in intelligent driving systems, Cheng et al. (2019) proposed an innovative deep learning approach.

This approach significantly enhanced the classification of road surface conditions meeting the demand for rapid and accurate roadway condition monitoring.

While the benefits of machine learning in infrastructure inspections are obvious, traditional machine learning algorithms do have disadvantages. They often necessitate massive volumes of labeled data for training, which can be time-consuming and expensive to obtain. To solve these obstacles, researchers and engineers are investigating alternative methodologies.

Transfer learning approaches enable the application of knowledge from models previously trained on tasks unrelated to the specific infrastructure inspection task at hand. Recently, researchers have intensified their focus on transfer learning as a means to augment the accuracy of roadway condition evaluation. This exciting avenue of research holds immense promise, enabling models trained on related tasks to be fine-tuned and applied to road condition analysis, thereby enriching the accuracy and robustness of the assessments.

Transfer learning is an advanced machine learning technique that enhances the performance of a model on a new, related task by leveraging knowledge gained from training on different tasks. Rather than starting from scratch, a pre-trained model is utilized as a starting point and then fine-tuned on the new task using a smaller, task-specific dataset. This approach is particularly valuable in scenarios where data are limited, where computational resources are constrained, or when aiming to achieve state-of-the-art performance across different domains (Zhuang et al. 2021, Salehi et al. 2023).

One notable example of transfer learning's success in roadway condition assessment comes from Brewer et al. (2021). Their innovative approach involved employing a pre-trained CNN model based on data collected in the United States for assessing roadway conditions in Nigeria. By adapting the US model with Nigeria-specific data, the researchers achieved an impressive 94.0% accuracy in predicting the quality of Nigerian roads. This showcased how transfer learning can effectively bridge the gap between different regions and adapt models to local conditions, leading to highly accurate predictions.

Additionally, Maarouf and Hachouf (2022) demonstrated the versatility of transfer learning by training a comprehensive CNN model using roadway condition images taken by smartphones in Japan. The researchers then fine-tuned this model for other countries by mixing the Japanese data with local data. This clever strategy allowed other countries to create efficient models based on the pre-trained Japanese model. By doing so, they harnessed the power of transfer learning to optimize the performance of their models, even with limited local data.

Project Goals and Objectives

The overarching goal of this project was to develop a convenient tool capable of evaluating slippery conditions on multi-lane roads in winter seasons. In achieving this goal, the project set forth the following objectives:

- Evaluate the feasibility of using dual-spectrum imagery for the assessment of slippery conditions on multi-lane roadways as follows:
  - Evaluate the effectiveness of optical images for roadway snow coverage estimation with sufficient illumination conditions
  - Evaluate the effectiveness of infrared images for roadway snow coverage estimation with poor illumination conditions
- Develop computer vision and machine learning approaches that can evaluate road surface conditions based on dual-spectrum imagery
- Develop a transfer learning technique that can evaluate road surface conditions based on a limited dataset of dual-spectrum imagery

While studies of winter road condition evaluation exist, none of the previously published work focuses on the use of optical and infrared images simultaneously for slippery roadway condition detection, which has the potential to operate in different illumination conditions.

Project Description/Summary

In this work, field data collection using a dual-spectrum camera was first performed at a field site in Utah. The research team analyzed optical and infrared images for a field of view (FOV) covering a multi-lane highway through several snowstorms. Image processing techniques, including image registration and segmentation, were implemented on both types of images. Moreover, the ratio of snow-covered pixels was computed to quantify the snow coverage rate of each lane. The team verified the system performance by comparing the estimations with the ground truth.

Furthermore, the researchers improved the efficiency of automated roadway snow detection systems through the utilization of transfer learning methodologies, specifically in scenarios where data availability was constrained. The research endeavored to enhance the efficiency and precision of snow detection on roadway surfaces in winter conditions by leveraging a blend of optical and thermal images. This was achieved through the implementation of the U-Net architecture within the Keras framework, which facilitated the development of a novel approach.

The present study aimed to provide empirical evidence supporting the notion that the proposed methodology exhibits enhanced efficacy in the realm of roadway snow detection, surpassing the capabilities of preceding systems while concurrently offering a viable solution to the obstacles presented by the scarcity of available data. The developed technique offers the potential to facilitate local agency decision-making in snow-plowing resource planning and performance evaluation and to enhance winter roadway safety.

Overview of Remaining Report Content

The subsequent chapters of this report provide detailed descriptions of the data collection, data processing, computer vision algorithms, transfer learning framework, model performance, and implementation recommendations.

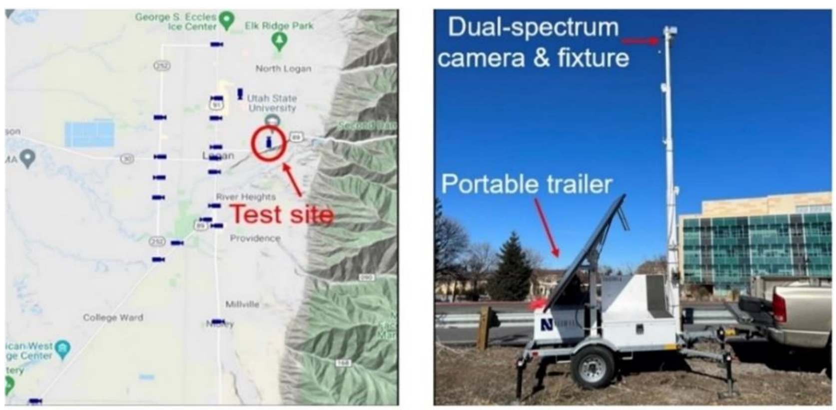
DATA COLLECTION

Objectives

The objective of the data collection effort was to create a dual-spectrum imagery dataset from two test locations in Utah to be used for roadway snow coverage estimation in this study. The research covered two winter seasons, and the research team used a different dual-spectrum camera for each winter.

Methods

Based on the expected precipitation and accessibility, the team identified a field test site for data collection close to the US 89 RWIS station in Logan, Utah, for the first winter season, as shown in Figure 1(a).



(a) (b)

Figure 1. (a) Test site close to US 89 RWIS station and (b) data collection setup for the first winter season

The InfiRay IRS-FB462A dual-spectrum bullet camera with an operating temperature ranging from -40°C to 70°C was selected for its endurance in the severe field environment. Its uncooled microbolometers cover a spectral range of 8 to 14 µm and support thermal imaging with a resolution of 640 by 512 pixels and an accuracy of ±2°C. The FOV of the infrared imager is 22° by 18°. Moreover, the optical lens of the camera provides a resolution of 1920 by 1080 pixels with a wider FOV compared to its infrared imager. This network camera simultaneously streams optical and infrared images with an interval of 1/25s, with the images directly transferred to and stored on a rugged laptop.

The dual-spectrum camera was attached to an extendable pole on the trailer via a customized fixture, which was lifted to approximately 10 ft (~3 m). The portable trailer continuously powered the data collection system with sets of batteries and solar panels, as shown in Figure 1(b).

This system operated at the field site from February 17, 2022, to April 15, 2022, during which two winter storms with significant accumulation of roadway snow were observed. The recorded optical and infrared images were regularly saved and transferred for further processing.

During the second winter season, the researchers performed data collection at a field site located near the I-80 Parleys Canyon RWIS station in Salt Lake City, Utah, as illustrated in Figure 2(a).

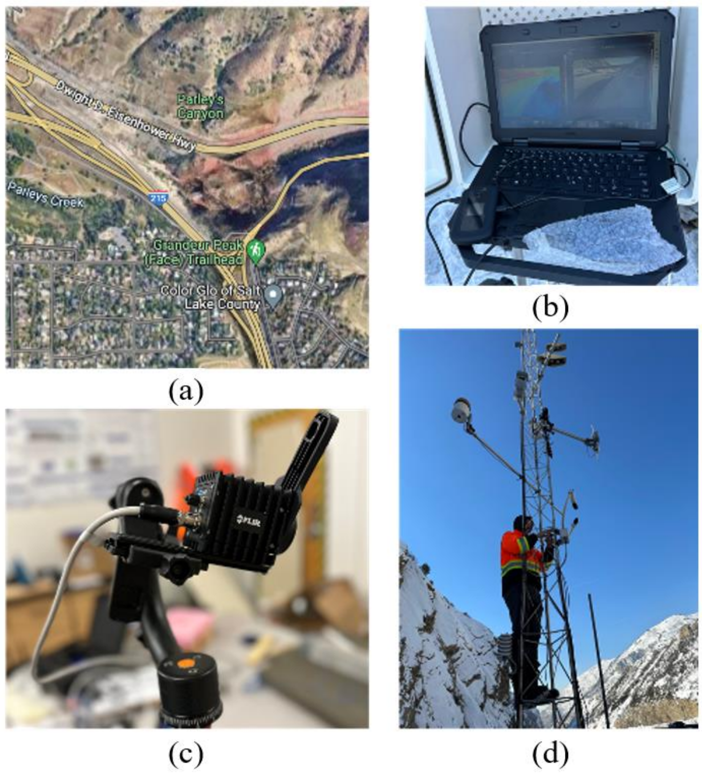


Figure 2. (a) Test site close to I-80 RWIS station, (b) data acquisition and storage system, (c) FLIR dual-spectrum camera, and (d) camera installation for the second winter season

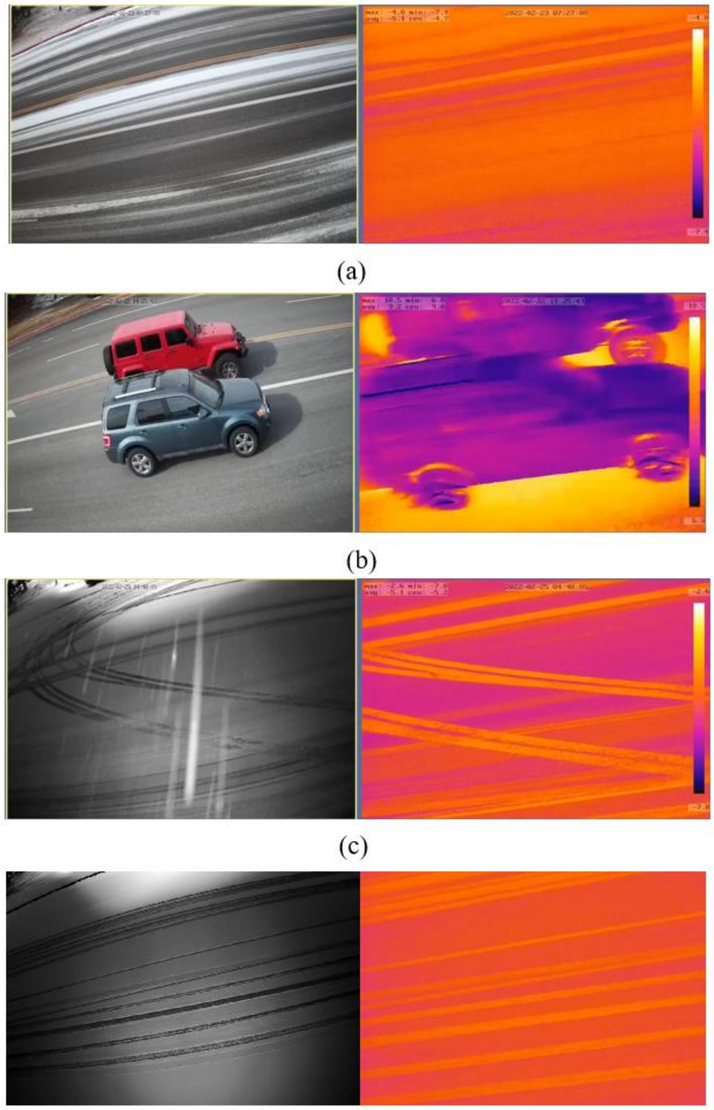
Initially, the team planned to use the fiber optics system owned by the Utah Department of Transportation (UDOT) for data communication. However, the internet protocol (IP) configuration of the FLIR A50 camera used at this site was not compatible with UDOT's system. Therefore, a local data acquisition and storage system was deployed for data collection, as shown in Figure 2(b).

Data collection was conducted using the compact thermal image streaming camera, FLIR A50, shown in Figure 2(c), which was chosen for its exceptional features tailored to winter road conditions. The camera's notable attributes include a frame rate of 30 Hz, a spectral range of 7.5 to 14.0 µm, a fixed focus with adjustable options, and a spatial resolution ranging from 1.2 to 4.0 mrad/pixel. With an infrared resolution of 464 by 348 pixels and a visual resolution of 1280 by 960 pixels, complemented by low thermal sensitivity (<35 mK for 29° and 51° FOV, and <45 mK for 95° FOV), the FLIR A50 excels at detecting temperature variations and capturing detailed imagery even in extremely cold conditions (ranging from -20°C to 175°C). Its accuracy of ±2°C or ±2% of readings ensures precise temperature measurements, while the simultaneous capture of infrared and optical images enables comprehensive analysis, making it an invaluable tool for winter road maintenance.

As shown in Figure 2(d), the camera was installed on the tower close to the RWIS station, and it operated continuously at the I-80 field site from November 14, 2022, to April 15, 2023, effectively capturing optical and infrared images during three winter storms characterized by significant roadway snow accumulation.

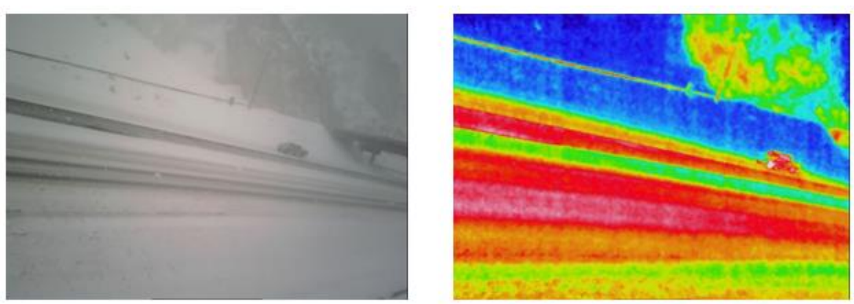
Results and Analysis

Representative dual-spectrum imagery, composed of optical and thermal images, is shown in Figures 3 and 4 for the first and second winter seasons, respectively. As shown in Figure 3, the research team covered five lanes with the optical lens and three lanes with the infrared lens. For the second winter season, the team covered both the eastbound and westbound lanes of I-80, but the eastbound lane was obviously better covered with more pixels.



(a) (b) (c) (d)

Figure 3. Daytime (a and b) and nighttime (c and d) dual-spectrum imagery collected during the first winter season



(a) (b)

Figure 4. Daytime dual-spectrum imagery collected during the second winter season

Based on both figures, the researchers summarized a few preliminary observations on the dual-spectrum imagery.

- The FOVs for the optical and infrared lenses are generally different, and the FOV of the optical lens covers a larger area compared to the FOV of the infrared lens. Therefore, the researchers would need to find the common FOV when performing pixel-level comparisons between optical and infrared images.

- During the daytime, optical images can generally support reasonable segmentation between snow-covered and non-snow-covered roadways. Since the textures of the snow-covered and non-snow-covered surfaces are easily distinguishable in these optical images, the researchers would use the optical images collected in the daytime for roadway snow detection. Also, infrared images collected in the daytime support less contrast between snow-covered and non-snow-covered roadways because the roadways reach thermal equilibrium at a faster rate. Moreover, both cameras were set with an auto range, which made them less sensitive to small temperature contrasts in the presence of vehicles and could be better handled in future studies.

- During the nighttime, optical images are generally less informative with poor or no illumination. However, the infrared images provided a clear temperature contrast between snow-covered and non-snow-covered roadways. As shown in Figure 3(c), the optical and thermal images collected during the first winter season (with streetlights) demonstrated that the infrared images are generally less affected by non-ideal illumination conditions, while the optical image quality was clearly impacted by the presence of snow.

- The researchers would use optical images captured during both daytime and nighttime (with streetlights) to generate the ground truth, based on which the team would develop and evaluate the algorithms. The optical and infrared images collected during the nighttime from the second winter season were not considered for study due to the lack of ground truth. Roadway ice detection was not performed due to the lack of ground truth from the optical images.

DATA PRE-PROCESSING

Objectives

The data pre-processing extended from the fact that the optical and infrared lenses do not perfectly align with each other and have different FOVs. The objective of the data pre-processing was to transform the infrared images so that their FOVs perfectly matched the ones from the optical images and to enable multi-lane assessment. Based on the data pre-processing results, the researchers generated the ground truth about snow coverage based on visual indications in the optical images collected during the daytime and nighttime (with sufficient illumination).

Methods and Results

Image Registration

Considering that the infrared lens has an FOV smaller than that of the optical lens, the team implemented image registration to align the FOV of the infrared images with that of the optical images. This process was necessary to support snow coverage estimation and performance comparison using both types of images. The team considered the affine transformation with cubic polynomials to register infrared images into optical ones. The transformation relations (Zitova and Flusser 2003, Szeliski 2010, Solomon and Breckon 2011) were assumed as follows:

$$x_i' = a_0 + a_1x_i + a_2y_i + a_3x_iy_i + a_4{x_i}^2 + a_5{y_i}^2 + a_6y_i{x_i}^2 + a_7x_i{y_i}^2 + a_8{x_i}^3 + a_9{y_i}^3 \quad \textbf{(1)}$$

$$y_i' = b_0 + b_1x_i + b_2y_i + b_3x_iy_i + b_4{x_i}^2 + b_5{y_i}^2 + b_6y_i{x_i}^2 + b_7x_i{y_i}^2 + b_8{x_i}^3 + b_9{y_i}^3 \quad \textbf{(2)}$$

where (x_i, y_i) are the coordinates of the ith pixel in a base or original infrared image (Figure 5(b)), and (x_i', y_i') are the coordinates of the same pixel in the corresponding optical image (Figure 5(a)).

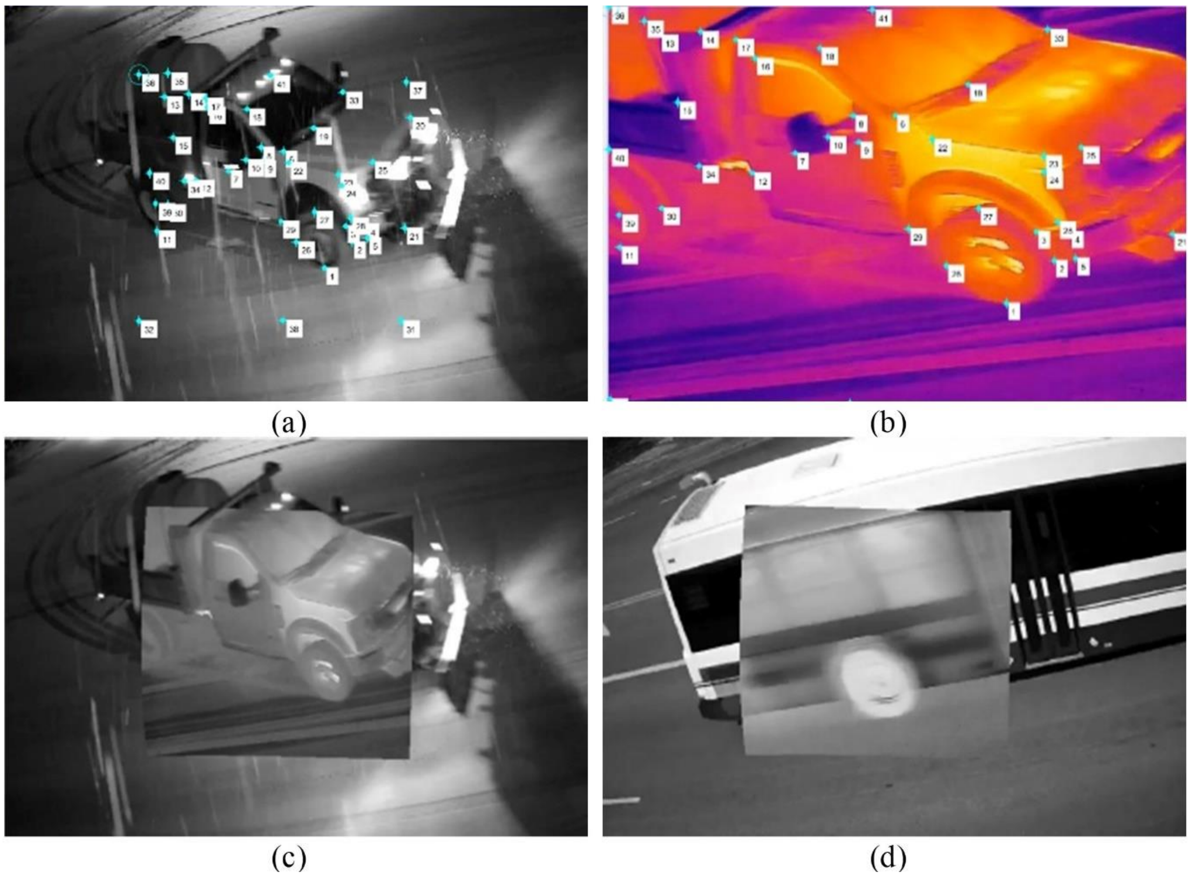


Figure 5. Selected control points in example (a) optical and (b) infrared images and the results (c and d) of image registration showing optical images overlaid with transformed infrared ones

By identifying sufficient geometrical feature points in an infrared image and the corresponding optical image, the coefficients a_k and b_k (k = 0, 1, 2, ..., 9) in equations (1) and (2) could be solved. Thus, the affine transformation matrix was determined.

The selected points in an infrared image and the corresponding optical image collected during the first winter season are shown in Figure 5(a and b). Since the performance of image registration strongly depends on selected feature points, the researchers determined the coefficients based on images with the most obvious geometrical features. The registration results with satisfactory alignment are shown in Figure 5(c and d), where the registered infrared images are overlaid with optical images.

Moreover, the team assumed that the perspective angle of the camera was fixed throughout data collection and that the relative positions of both lenses were consistent during the data collection process. Therefore, the optimal affine matrix based on the selected images was applicable to all infrared images.

Figure 6 illustrates the image registration process for the second winter season, showcasing the precise alignment of thermal and optical images from the I-80 test site using the affine transformation model represented in equations (1) and (2).

(a) (b) (c)

Figure 6. Image registration process involving (a) an infrared image, (b) an optical image, and (c) the corresponding registered image with an emphasis on the eastbound lane

In this case, the researchers focused on the I-80 eastbound lane for better lane coverage.

Lane Splitting Using Segmentation and Morphological Operation

With the field test setup, the FOV of the infrared imager generally covered three lanes, which enabled multi-lane snow coverage estimation. In this study, the team analyzed three lanes individually with the help of a lane splitting process. The general idea was to determine the boundaries between lanes in images without snow or vehicles. Thus, a clean optical image was first segmented, followed by a morphological operation where simply connected regions were determined. The lane splitting process is demonstrated in Figure 7.

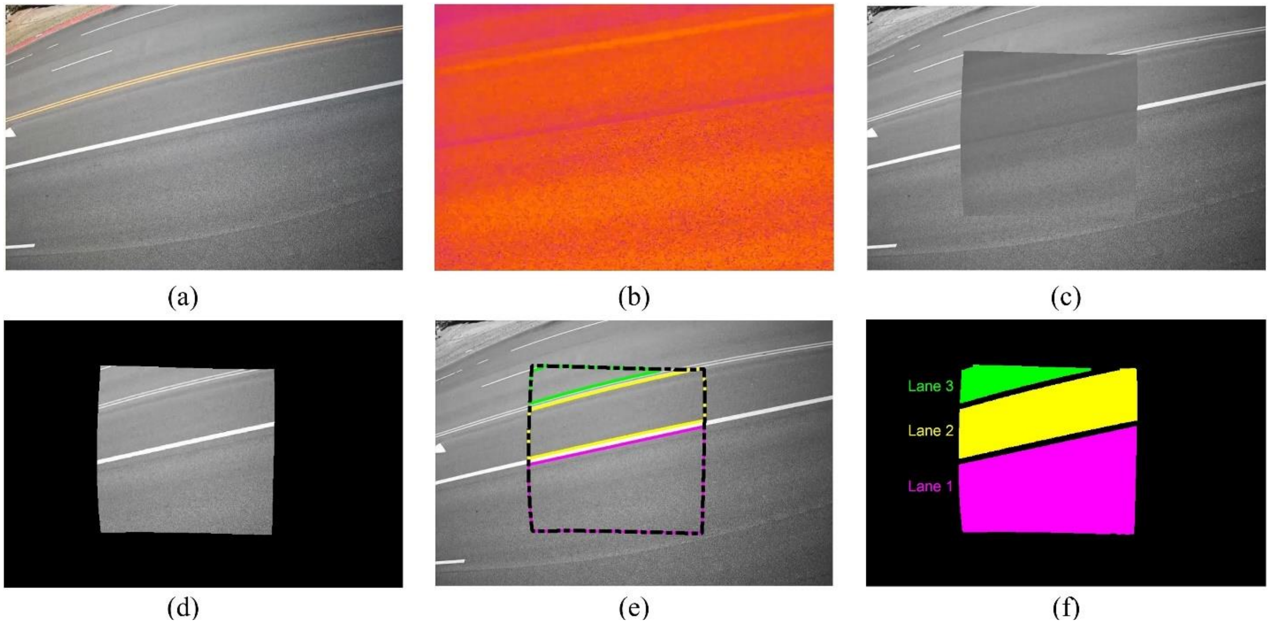


Figure 7. Lane splitting process: the original (a) optical and (b) infrared images of a clean roadway, (c) the optical image overlaid with the registered infrared image, (d) cut of the optical image with the FOV of the registered infrared image, (e) lane boundaries, and (f) pixels for individual lanes

The original optical and infrared images are shown in Figure 7(a and b) with a clear view of the roadway. The infrared image was first registered into the optical image, and the result is shown in Figure 7(c). Second, an image cut on the optical image with the same FOV as the registered image was performed. The cut optical image (Figure 7(d)) was then converted into a binary image by assigning cluster numbers to pixels from the segmentation. After a series of morphological operations on Figure 7(d), including erosion and dilation, three simply connected regions corresponding to the three lanes were successfully identified: Lane 1 (pink) is the middle lane of eastbound US 89, Lane 2 (yellow) is the left-turn lane of eastbound US 89, and Lane 3 (green) is the left lane of westbound US 89. Finally, the boundaries and pixels of individual lanes are shown in Figure 7(e and f). The proposed process applies to more general and complex scenarios than simple line detection and fitting.

For the data collected during the second winter season, the researchers conducted lane splitting on road imagery with the objective of evaluating the degree of snow accumulation within individual lanes. The exact locations of the white lines that delineate the lanes on the roadway were manually extracted, taking into account the fixed position of the camera. Figure 8 demonstrates an image in which each lane has been labeled.

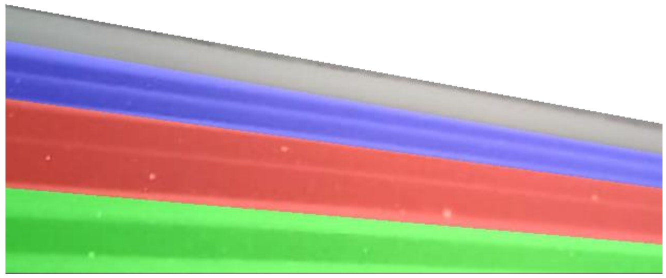


Figure 8. Individually labeled lanes for assessing roadway snow coverage in the second winter season

By employing the extracted coordinates, the researchers proceeded to implement the technique of lane splitting on supplementary images, thereby facilitating a granular analysis of snow accumulation within each lane. The utilization of this particular methodology yielded significant findings pertaining to the extent of snow coverage in specific lanes.

Image Labeling

To evaluate the performance of the proposed methods, the researchers established the ground truth and compared it with the segmentation results. In this study, the Image Labeler, an application built in MATLAB, was used to manually mark snow-covered pixels. A typical optical image and the ground truth collected in the daytime are shown in Figure 9(a and b). Pixels with the color white, except the pavement markings, were highlighted with the Image Labeler in green.

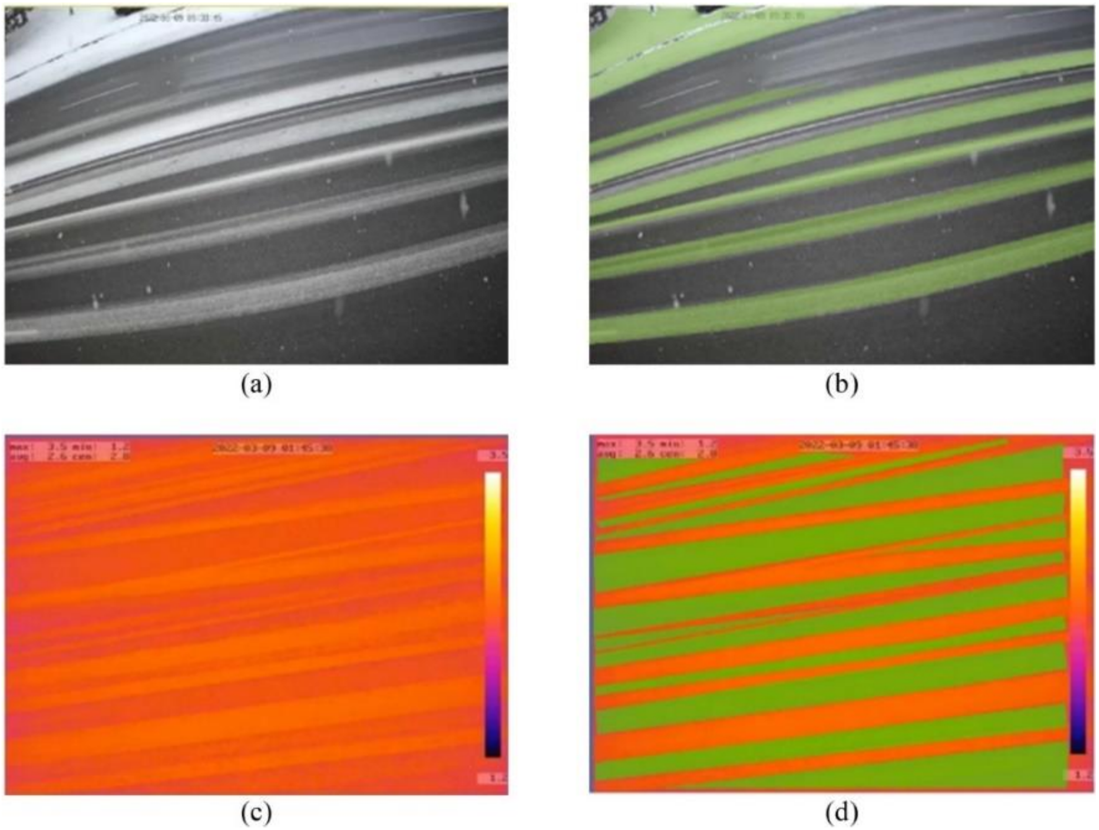


Figure 9. (a) Original optical image and (b) marked ground truth and (c) original infrared image and (d) marked ground truth, where snow is marked in green

A typical infrared image and its ground truth are marked in Figure 9(c and d), where the pixels with lower temperatures are marked as snow in green. The snow-covered area demonstrates an excellent contrast due to high temperature contrasts, which is confirmed by its corresponding optical image.

SNOW COVERAGE ESTIMATION USING COMPUTER VISION

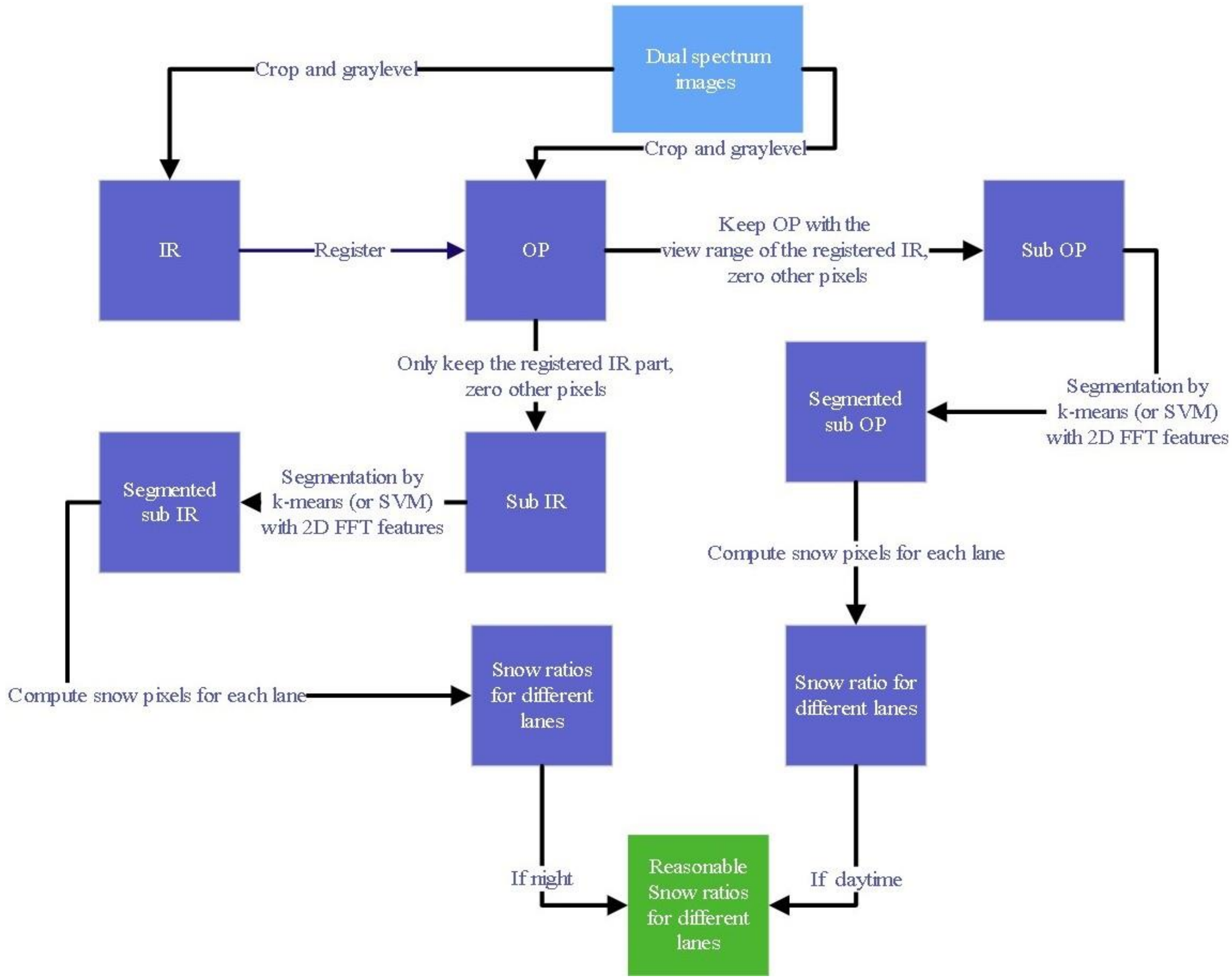
Objectives

Based on the pre-processed data, the team developed a computer vision framework that uses spectrum features of optical and infrared images and unsupervised and supervised machine learning methods to estimate the snow coverage on the roadway. Due to the limited data volume, the researchers adopted k-means clustering and SVM rather than deep learning-based algorithms. The performance was evaluated via confusion matrices based on the ground truth established as described in the previous chapter.

Methods

Image Segmentation

Combining the developed functions and modules, the roadway snow detection process is summarized in Figure 10.



IR = infrared images and OP = optical images

Figure 10. Workflow of roadway snow coverage estimation

With the input of dual-spectrum images and the output of snow coverage for individual lanes, the framework used image registration to achieve a common FOV between the infrared and optical images. The team adopted morphological operations to identify the pixels of individual lanes and used two-dimensional (2D) fast Fourier transform (FFT) to extract feature vectors, followed by unsupervised k-means clustering and supervised SVM for image segmentation. Once the segmentation was completed, roadway snow coverage could be estimated by calculating the ratio of the number of snow-covered pixels over the number of total pixels in each lane.

With image registration, the optical and infrared images shared a set of pixels that covered a common area with minimized distortions. The team implemented image segmentation for roadway snow coverage estimation based on image textures in the optical and registered infrared images. Image textures are a set of metrics to quantify the perceived patterns in an image and supply information about the spatial arrangement of colors or intensities in the image (Shapiro and Stockman 2001).

In this study, the power spectrum in the frequency domain of pixel intensities was considered to represent the texture features, and the team implemented discrete 2D FFT (Gonzalez 2018) to compute the texture features of a small sliding window across the entire image using the following equation:

$$F(u,v) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-2\pi i\left(\frac{ux}{M}+\frac{vy}{N}\right)} \quad \textbf{(3)}$$

where $f(x,y)$ is the intensity function of an image of size of M by N, (x, y) are the coordinates of pixels, and (u, v) are the wavenumbers for the x and y directions. For each pixel, the researchers computed the power spectrum via discrete 2D FFT of a 5-by-5 sub-window, whose center is located at a specific pixel. The spectrum was then converted into a 25-by-1 vector, which represents the texture feature of the central pixel. The same procedure was repeated on pixels over the entire image.

The resulting feature vectors were then fed into the k-means clustering algorithm, where the sum of the Euclidean distance between the feature vectors and the mean vector or centroid among each cluster was minimized iteratively until the minimum was achieved. The centroid of each cluster was then determined. Finally, all the pixels in the image were labeled by their cluster numbers to generate a mask.

As an alternative to k-means clustering, SVM was employed for image segmentation. This supervised learning technique seeks to classify data with a hyperplane, where the generalization error of the constructed decision function is minimized. The image features of each pixel can be extracted from the specific pixel and its neighbors based on equation (3). Moreover, all pixels in an image were classified by SVM considering the nonlinear case and using a Gaussian radial basis function.

Results and Analysis

Due to the limitations of the specific camera and dataset, the team adopted different strategies for roadway snow detection during the daytime and nighttime. Optical images collected during the daytime and infrared images collected during the nighttime were analyzed.

Snow Coverage Estimation Using Optical Images

During the daytime, with sufficient illumination conditions, the textures of snow-covered roadways in optical images support higher contrasts compared to the textures in infrared images. For the ease of comparing optical and infrared images, pixels within the FOV of registered infrared images in the optical images were considered. The 25-by-1 2D FFT feature vectors of the optical and infrared images were calculated. The original optical and infrared images are shown in Figure 11(a, d, and g).

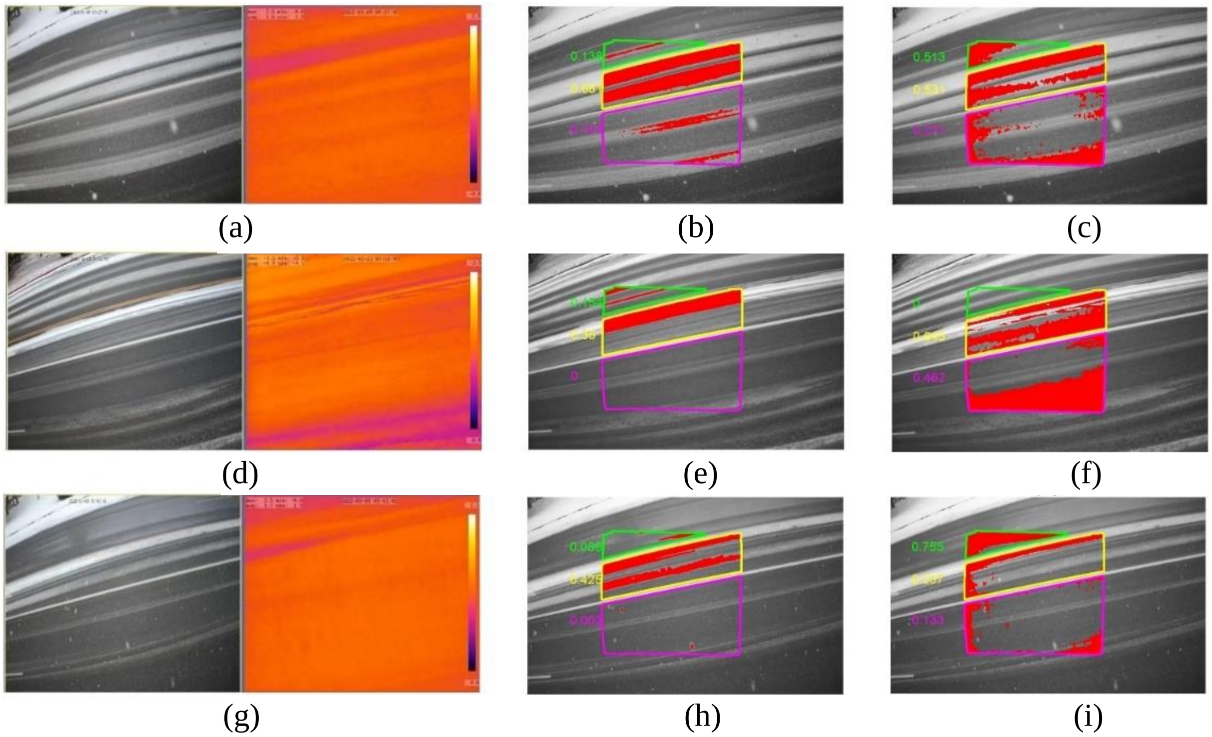


Figure 11. Results of snow segmentation during the day: (a) original image set 1 and its corresponding segmentation results based on (b) optical and (c) infrared images, (d) original image set 2 and its corresponding segmentation results based on (e) optical and (f) infrared images, and (g) original image set 3 and its corresponding segmentation results based on (h) optical and (i) infrared images

With the proposed image segmentation technique, the contours of the snow-covered area were appropriately identified and highlighted in red based on the optical images, as shown in Figure 11(b, e, and h). Moreover, the snow coverage ratio of each lane generally indicated the amount of snow left on the lane. The snow coverage ratios of Lanes 1 (pink) and 3 (green) were usually lower than that of Lane 2 (yellow). Considering that Lane 2 was a left-turn lane, it experienced less traffic than the other two passing lanes.

As a comparison, the results of segmentation based on the corresponding infrared images are also shown in Figure 11(c, f, and i). The results were not satisfactory because the snow-covered areas (indicated by red pixels) considerably differed from the snow patterns in the optical images. The distribution of snow was also not correctly reflected. The misclassification of the snow may be attributed to the small temperature difference or the low contrast of the temperature distribution.

One issue with segmentation in the optical images was that falling snowflakes were identified as snow on the road, as shown in Figure 11(h). This resulted from the fact that the roadway snow and falling snowflakes shared a similar level of pixel intensity. This was negligible for the dataset at hand, though the influence of heavy snow needs to be considered in the future.

The snow coverage ratios over a period of time are shown in Figure 12.

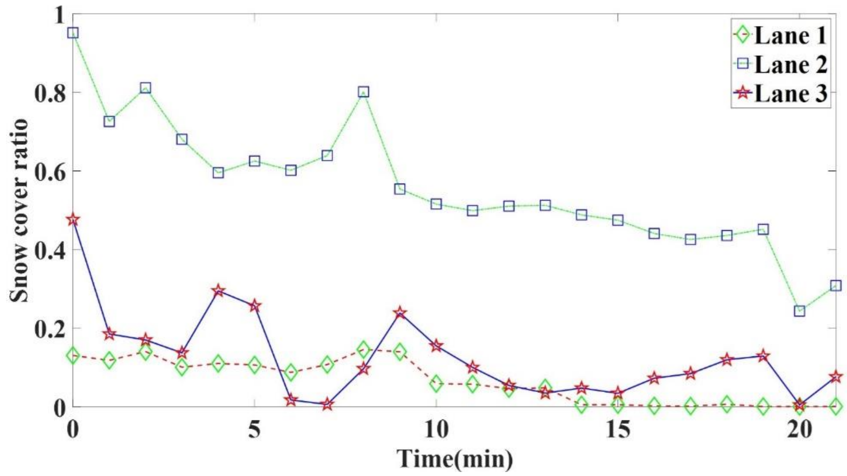


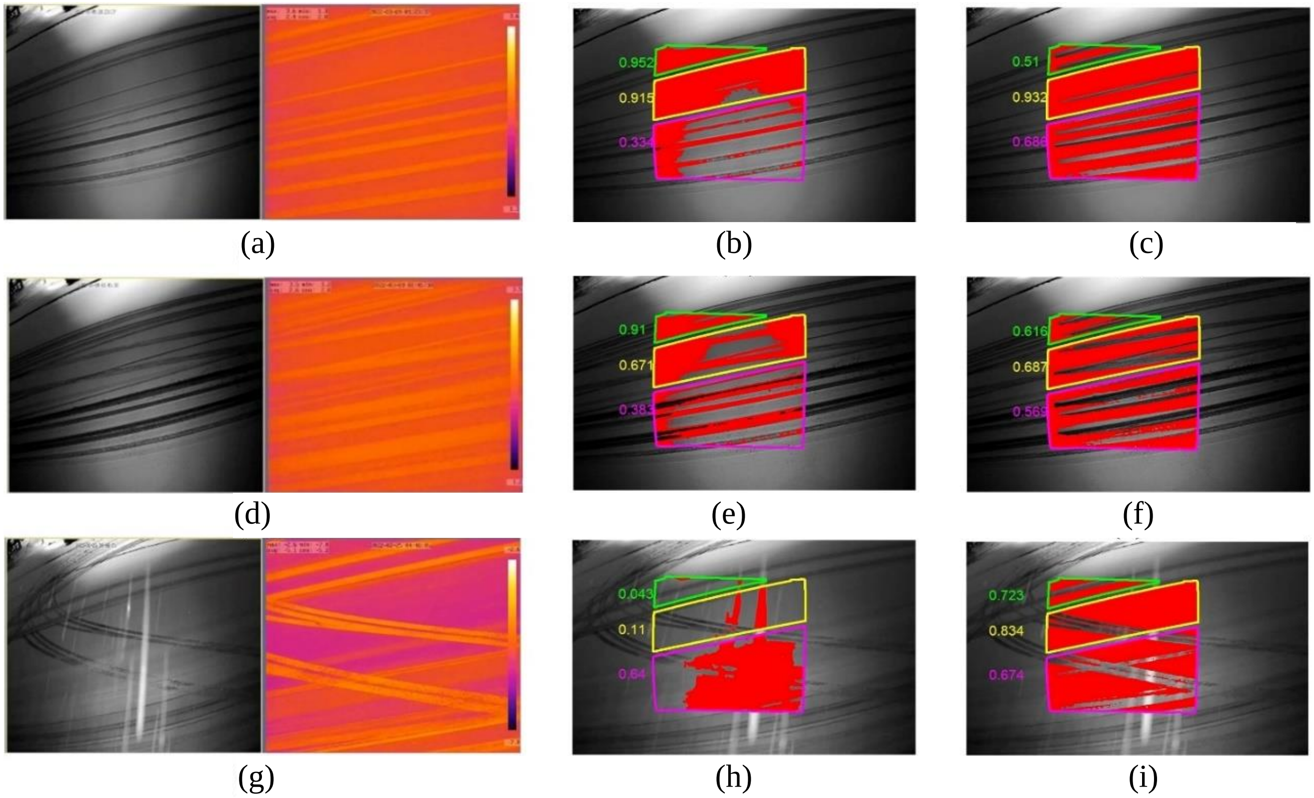
Figure 12. Snow coverage ratios of the optical images during the day

The segmentation process was designed to be automated. However, the auto-segmentation of images poses a great challenge due to the difficulty of adapting real-world changes to the computer vision system (Bhanu et al. 1995). The team identified the clusters of snow-covered regions using the gray-level optical image based on a simple idea: the pixels of one cluster with a higher average pixel intensity than other clusters were considered to be a snow-covered region.

For Figure 12, the images were extracted from the video every minute. The total monitoring time with the presence of roadway snow was 21 minutes, which demonstrated that the snow melted as time passed. Thus, the snow coverage ratio descended with time. Again, as shown in Figure 12, Lane 2 had a higher snow coverage ratio than the other two lanes due to less traffic.

Snow Coverage Estimation Using Infrared Images

During the nighttime, illumination from streetlights was limited, and the textures extracted from optical light intensity could no longer serve as ideal feature vectors. In this case, the researchers used infrared images for snow coverage estimation. The infrared images were processed using the same procedures described in the previous section. The original optical and infrared images are shown in Figure 13(a, d, and g).



Snow is marked as red

Figure 13. Results of snow segmentation at night: (a) original image set 4 and its corresponding segmentation results based on (b) optical and (c) infrared images, (d) original image set 5 and its corresponding segmentation results based on (e) optical and (f) infrared images, and (g) original image set 6 and its corresponding segmentation results based on (h) optical and (i) infrared images

With the help of vivid streetlights, the researchers observed a general pattern of roadway snow coverage. This was confirmed by the segmentation results using optical images in Figure 13(b, e, and h). However, the snow-covered regions were sometimes misclassified due to generally poor illumination levels and low pixel intensities. More importantly, the infrared images demonstrated excellent contrast between the snow-covered and not-snow-covered areas. Segmentation using the infrared images showed excellent agreement with the snow patterns, as shown in Figure 13(c, f, and i).

The obvious shift and slight distortion in Figure 13(c and f) is notable. This could be due to the motions of the camera. While the camera was attached to a pole through a rigid fixture, the perspective angle of the camera could change slightly on occasion given traffic-induced vibrations or wind. This would induce small variations in the affine transformation matrix. Mitigation is possible with sufficient geometric features. However, it was not necessary for this study since the researchers were not cross-validating the snow coverage using both optical and infrared images.

As expected, falling snowflakes caused an issue of misclassification in the optical images, as shown in Figure 13(h). Fortunately, the infrared images were less influenced by unfavorable illumination conditions and snowy weather, as shown in Figure 13(g).

The snow coverage ratios for each lane at night were also calculated through image segmentation using infrared images from a 36-minute-long video. As shown in Figure 14, the snow coverage ratios indicated a change of snow area every two minutes.

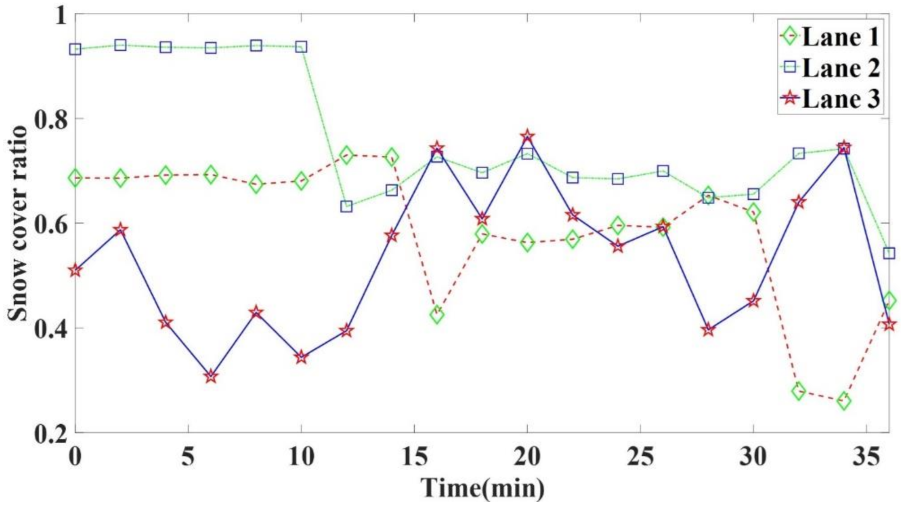
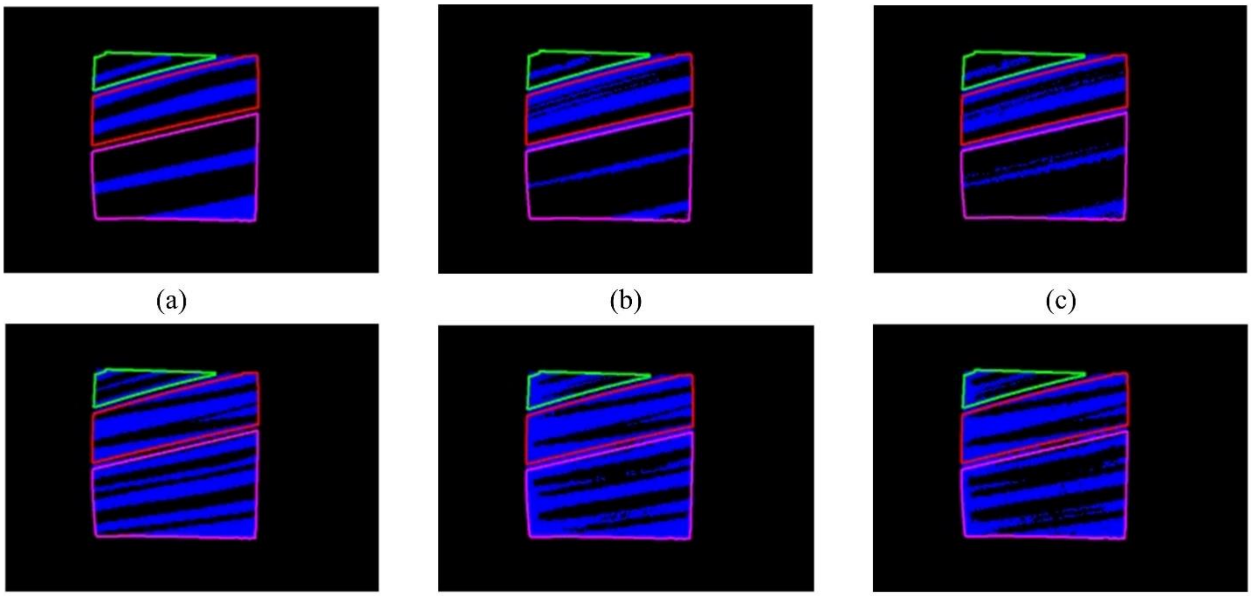


Figure 14. Snow coverage ratios based on infrared images collected at night

Also, the snow coverage ratios at night descended much more slowly than during the day. This is because the traffic is less frequent and the melting process is slower at night.

The researchers evaluated the performance of the proposed technique by comparing the segmentation results with the corresponding ground truth, as shown in Figure 15.



(a) (b) (c)

(d) (e) (f)

Snow-covered pixels marked in blue

Figure 15. Image segmentation on an optical image with (a) manually marked ground truth, (b) segmentation results by k-means clustering, and (c) segmentation results by SVM; image segmentation on an infrared image with (d) manually marked ground truth, (e) segmentation results by k-means clustering, and (f) segmentation results by SVM

In both the cases of optical and infrared images, the segmentation results generally agreed well with the ground truth. Misclassifications usually occurred at the boundaries between snow-covered and not-snow-covered regions. Furthermore, the confusion matrices for each of the six images and each lane were computed individually to quantify performance (Murphy 2012), with results shown in Tables 2 through 4 for Lanes 1 through 3, respectively.

Table 2. Performance of k-means clustering on Lane 1 with representative images

Image Number	Accuracy	Precision	TPR	TNR
Im 1	0.7340	0.8624	0.2576	0.9789
Im 2	0.8183	0.7827	0.4189	0.9590
Im 3	0.9981	NA	NA	0.9981
Im 4	0.9167	0.9119	0.9647	0.8282
Im 5	0.8573	0.8533	0.8919	0.8158
Im 6	0.9150	0.9775	0.9115	0.9273

TPR = true positive rate; TNR = true negative rate; NA = not applicable (no snow)

Table 3. Performance of k-means clustering on Lane 2 with representative images

Image number	Accuracy	Precision	TPR	TNR
Im 1	0.9039	0.9863	0.8858	0.9612
Im 2	0.8724	0.7973	0.9632	0.7972
Im 3	0.8360	0.8888	0.7638	0.9066
Im 4	0.9609	0.9692	0.9887	0.6677
Im 5	0.9189	0.9004	0.9800	0.8145
Im 6	0.8924	0.8986	0.9703	0.6275

TPR = true positive rate; TNR = true negative rate

Table 4. Performance of k-means clustering on Lane 3 with representative images

Image number	Accuracy	Precision	TPR	TNR
Im 1	0.7159	0.7646	0.2937	0.9499
Im 2	0.8296	0.7223	0.6130	0.9112
Im 3	0.9169	0.1496	0.5625	0.9252
Im 4	0.7996	0.8413	0.7808	0.8222
Im 5	0.6053	0.5230	0.7620	0.4903
Im 6	0.8472	0.7970	0.9712	0.6937

TPR = true positive rate; TNR = true negative rate

Specifically, the researchers highlighted the metrics of accuracy and precision for performance evaluation. Accuracy is the fraction of correct model predictions. For binary classification, accuracy represents the ability of the model to make correct predictions, as follows:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ number\ of\ predictions} \quad \textbf{(4)}$$

where true positives are the number of correctly predicted instances of the target objects (i.e., the number of objects that were correctly identified as positive by the model), and true negatives are the number of instances where the model predicted the non-presence of an object that was actually not present in the ground truth.

Precision measures the accuracy of model predictions by calculating the proportion of correctly predicted positive samples (true positives) out of the total predicted positive samples. Thus, precision represents the ability of the model to avoid false positives. Precision is calculated as follows:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \quad \textbf{(5)}$$

where false positives are the number of instances where the model predicted the presence of an object that was actually not present in the ground truth.

Overall, the proposed technique supported excellent accuracy and precision, particularly for Lanes 1 and 2. Since the pixels for these two lanes covered sufficiently large areas, the variances in snow-covered regions were smaller than that for Lane 3. The accuracies over the six images were mostly above 80%, demonstrating the effectiveness of the algorithm.

Because barely any snow was present in Lane 1 in image 3, the precision and true positive rate related to snow pixels was not applicable in this situation. The performance was dominated by the contrast of pixel intensity or temperature. Therefore, errors such as misclassification were generally inevitable when the illumination was not uniform or when the temperature contrast was small. This issue could be mitigated in future work that involves supervised learning with a larger data volume.

To thoroughly test the 2D FFT texture features, all labeled optical and infrared images were analyzed using unsupervised k-means clustering and supervised SVM methods. The ground truth of this dataset was also obtained using the Image Labeler application in MATLAB.

For SVM, the training process was realized by using a cross-validation approach. Half of the images were used for training, while the rest were used for testing. Semantic segmentation was performed at the pixel level to group all pixels into snow-covered or not-snow-covered classes.

The performance of both k-means clustering and SVM on these images is shown in Tables 5 through 8, where the researchers considered all of the pixels in specific lanes from all of the images in the dataset.

Table 5. Overall performance of k-means clustering on the dataset of optical images

Region of Interest	Accuracy	Precision	TPR	TNR
Lane 1	0.8707	0.3201	0.8884	0.8694
Lane 2	0.8746	0.9252	0.8438	0.9136
Lane 3	0.8725	0.4993	0.5525	0.9192
Overall	0.8722	0.6938	0.8363	0.8835

TPR = true positive rate; TNR = true negative rate

Table 6. Overall performance of SVM on the dataset of optical images

Region of Interest	Accuracy	Precision	TPR	TNR
Lane 1	0.8922	0.4953	0.8397	0.8985
Lane 2	0.8465	0.9203	0.8060	0.9029
Lane 3	0.8560	0.6564	0.4916	0.9404
Overall	0.8788	0.6947	0.8263	0.8941

TPR = true positive rate; TNR = true negative rate

Table 7. Overall performance of k-means clustering on the dataset of infrared images

Region of Interest	Accuracy	Precision	TPR	TNR
Lane 1	0.8318	0.9105	0.7914	0.8893
Lane 2	0.9102	0.9690	0.9112	0.9072
Lane 3	0.6708	0.8209	0.4853	0.8803
Overall	0.8437	0.9134	0.8166	0.8923

TPR = true positive rate; TNR = true negative rate

Table 8. Overall performance of SVM on the dataset of infrared images

Region of Interest	Accuracy	Precision	TPR	TNR
Lane 1	0.8464	0.8432	0.8540	0.8386
Lane 2	0.9109	0.9324	0.9425	0.8342
Lane 3	0.7174	0.6904	0.5386	0.8376
Overall	0.9586	0.8747	0.8534	0.9778

TPR = true positive rate; TNR = true negative rate

The research team evaluated the four indices: accuracy, precision, true positive rate, and true negative rate. In general, the differences between the performance of k-means clustering and SVM were negligible. Similar to the results shown Tables 2 through 4, the performance on individual lanes differed, which could be attributed to the lack of image coverage for Lane 3. The overall true positive rate (where a positive case represents snow) was above 80%, which is comparable to the performance found in the existing literature (Khan and Ahmed 2019).

SNOW COVERAGE ESTIMATION BASED ON TRANSFER LEARNING

Objectives

The objective of this research was to improve the efficiency of automated roadway snow detection systems through transfer learning methodologies to address the challenges imposed by the limited data volume. The researchers used the pre-trained neural network that was trained based on large-scale labeled datasets, which has existing capabilities of edge detection, object identification, and image segmentation. By training a small set of hyperparameters within the trainable hidden layers with a limited-volume dataset, the transfer learning algorithm has the potential for roadway snow detection with enhanced performance compared to the computer vision approach described in the previous chapter.

Methods

For the transfer learning methodology utilized in this study, the research team employed the U-Net architecture within the Keras framework. Transfer learning enabled the team to harness the capabilities of a pre-existing U-Net model that was tailored explicitly for image segmentation and to customize it to suit this particular problem domain.

The U-Net architecture is well known for its capacity to precisely define object boundaries in images, making it an excellent option for locating snow-covered road areas. By initializing the U-Net architecture with pre-trained weights obtained from a substantial dataset, the researchers were able to utilize the acquired knowledge from a wide variety of images. This initialization process facilitated the model to effectively capture low-level and high-level features pertinent to the specific task.

In order to adapt the U-Net model to this particular application, the researchers conducted fine-tuning of the final layers to acquire snow-specific features from the research dataset. Furthermore, the team opted to freeze most of the initial layers to maintain the overall feature extraction capabilities and mitigate the risk of overfitting, given the constraints of the limited snow dataset. Figure 16 shows the transfer learning model architecture implemented for roadway snow detection.

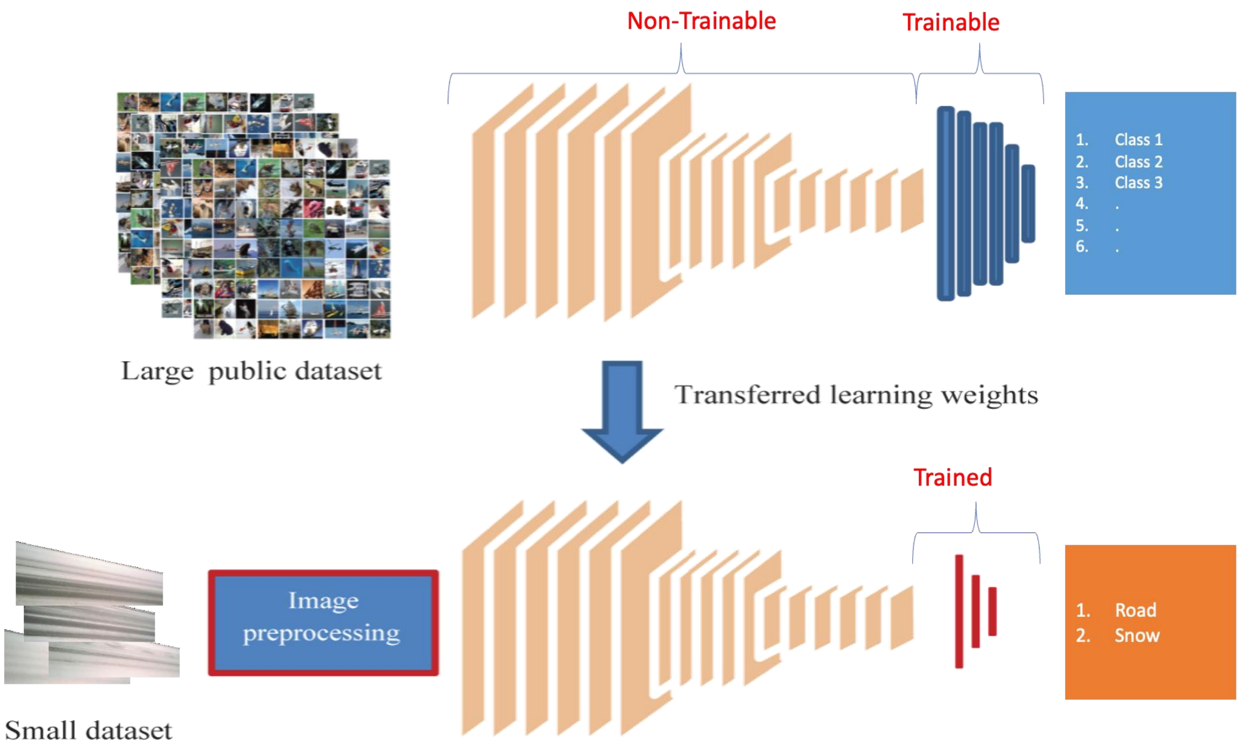


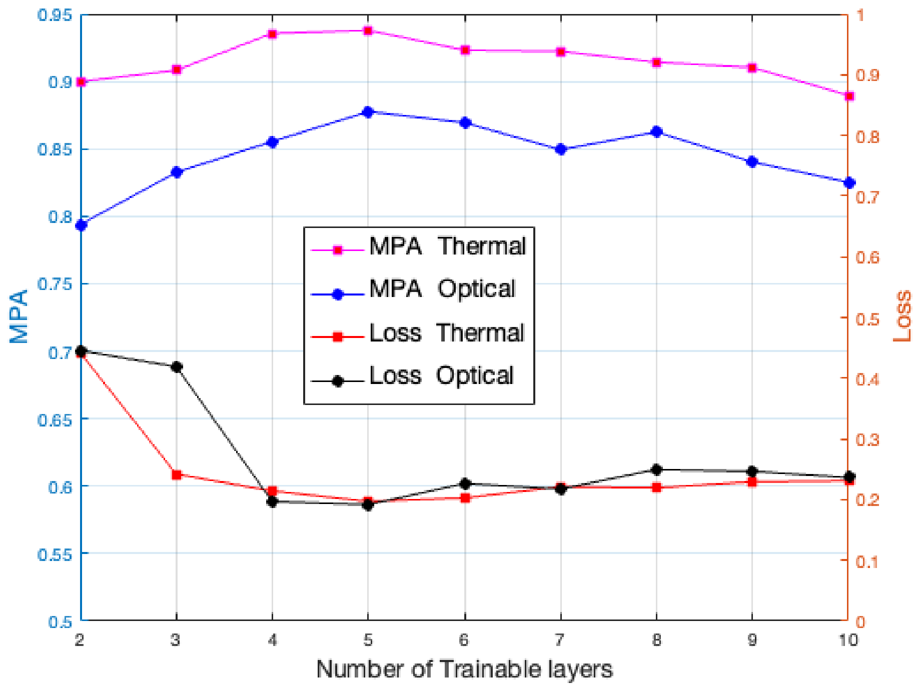
Figure 16. Transfer learning model architecture

The team assessed the performance of the model by using both quantitative and visual assessment techniques. The researchers used a U-Net architecture to train the model. The U-Net was initially trained on a large dataset and then fine-tuned specifically for the image segmentation task. In order to evaluate its performance in a quantitative manner, the researchers calculated the categorical cross-entropy loss using a distinct test dataset. The model's ability to accurately segment objects in nighttime images improved as the loss decreased. In addition, the researchers computed the mean pixel accuracy (MPA) to assess the accuracy of segmentation, which is equivalent to the precision defined in equation (5).

In addition, the team saved the predicted segmentation masks and original test images to an output directory to gain visual insights into the model's segmentation capabilities. This allowed the researchers to evaluate the model's ability to capture the objects of interest in nighttime scenes by visually inspecting the images. By utilizing both quantitative metrics and visual evaluation, the researchers were able to gain a comprehensive understanding of how well the transfer learning model performed and its capability to generalize to nighttime images that the model had not characterized before. The evaluation process allowed the researchers to assess the model's segmentation performance and identify its strengths, weaknesses, and areas that could be improved further.

Results and Analysis

The aim of this research study was to develop an efficient and accurate model for detecting snow-covered roads using both thermal and optical images. The researchers employed transfer learning to leverage pre-trained models and investigate the impact of the number of trainable layers on the training process, MPA, and test loss. The experiment involved varying the number of trainable layers in the model and analyzing its effect on the training process. Figure 17 reveals that setting the trainable layers to five led to the highest MPA and the lowest test loss for both the optical and thermal image-based models.



MPA = mean pixel accuracy

Figure 17. Assessing model performance using various trainable layers and datasets, including both optical and thermal images

This outcome indicated that striking a balance in the complexity of the model by controlling the number of trainable parameters was crucial for achieving optimal performance. The model’s performance with five trainable layers (the optimal layer design) is shown in Table 9.

Table 9. Performance of optimal transfer learning model with five trainable layers

Image Type	Test Loss (min)	MPA (max)
Optical	0.21	0.94
Thermal	0.21	0.88

MPA = mean pixel accuracy

The performance of the model was assessed in terms of the imaging modality used (thermal and optical images). Optical images displayed superior results during the daytime due to their higher resolution and ample illumination. In contrast, the performance of the model with thermal images was slightly impacted during the nighttime. Nonetheless, the MPA for the thermal image-based model remained at an acceptable level of 0.88, demonstrating its reliability under challenging conditions.

The study also examined the impact of dataset size on model performance. Surprisingly, as Figure 18(a) indicates, the model exhibited excellent performance even with a very small dataset.

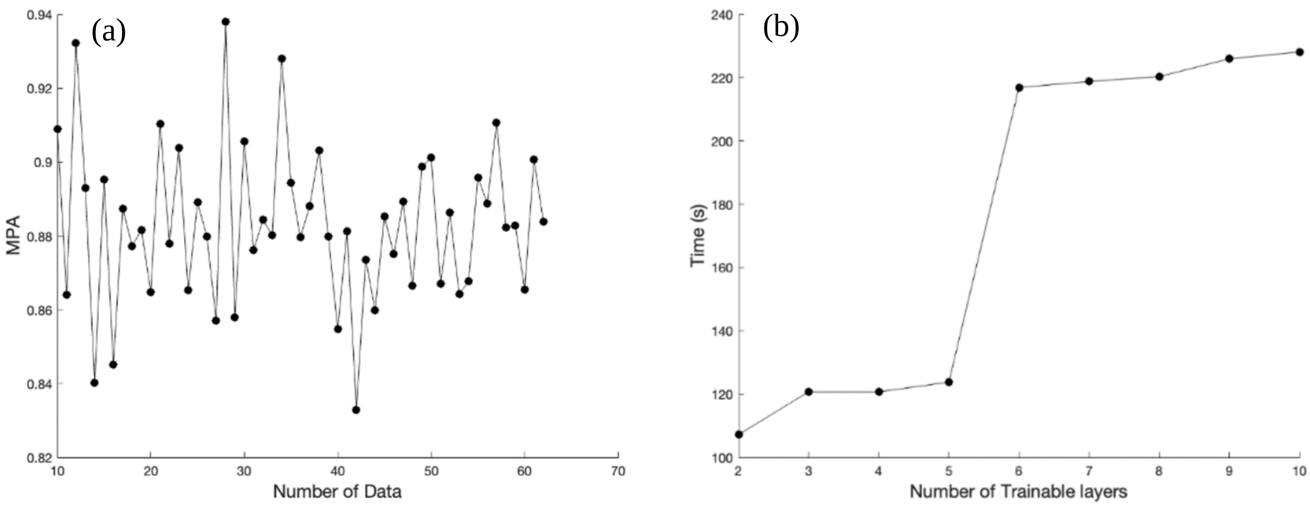


Figure 18. Parametric study: (a) performance evaluation with various numbers of data and (b) relationship between training time and the number of trainable layers

As the dataset size was increased from 10 to 64 images, no significant improvement in the model's performance was observed. This finding emphasized the effectiveness of transfer learning in leveraging pre-trained knowledge with limited training data. On the other hand, while a smaller dataset was sufficient to achieve good results, the trade-off was noticeable in terms of training time. As Figure 18(b) demonstrates, the time required for model training escalated significantly as the number of trainable layers increased. Researchers and practitioners must consider this trade-off when deploying the system, as larger datasets may demand more computational resources and time for training.

As shown in Figure 19, the predictions of the transfer learning model demonstrated the successful utilization of thermal and optical images for snow detection on roadways in both winter seasons.

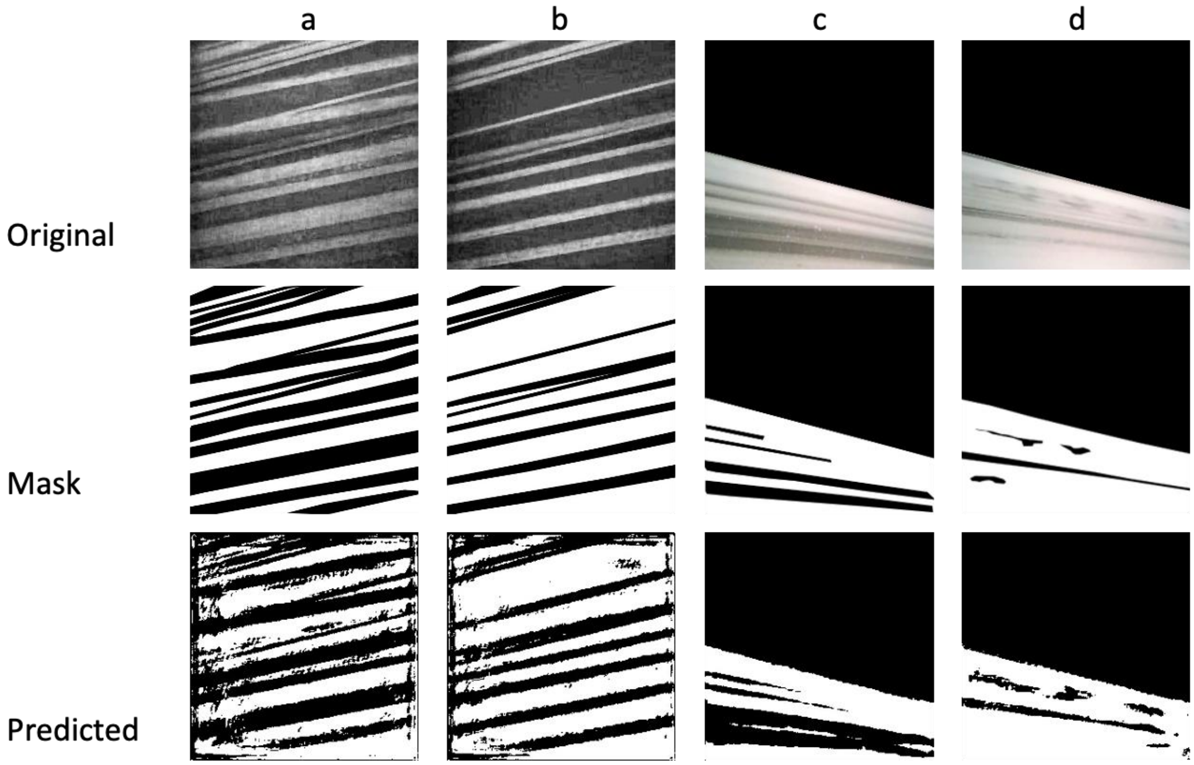


Figure 19. Model predictions alongside the mask (ground truth) and original images: (a and b) examples of thermal images recorded at night from the US 89 test site and (c and d) examples of optical images captured during the daytime from the I-80 test site

By employing transfer learning, the team achieved efficient and accurate predictions. In cases where manual labeling failed to capture the complex geometries of the roadway snow, the model prediction provided more reasonable and accurate classifications between snow-covered and non-snow-covered surfaces, as shown in Figure 19(c and d). Adopting the optimal number of trainable layers proved to be essential in optimizing the model's performance, as it influenced the model's complexity and generalization capabilities.

Table 10 evaluates the precision of different machine learning models for the task of roadway snow detection.

Table 10. Performance of three distinct machine learning approaches for detecting roadway snow based on data collected from the US 89 test site

MPA (Precision)	Optical	Thermal
Transfer learning	0.94	0.88
K-means clustering	0.69	0.91
Support vector machines	0.69	0.87

MPA = mean pixel accuracy

Precision is a metric used to measure the proportion of true positive predictions among all positive predictions made by the model. In this context, precision indicates how accurate the models (transfer learning, k-means clustering, and SVM) were in identifying instances of roadway snow using both optical and thermal images.

The transfer learning model demonstrated notable performance in terms of precision for both optical and thermal images, achieving a precision score of 0.94 and 0.88, respectively. The high precision scores indicate that the model exhibited a commendable level of effectiveness in accurately detecting instances of roadway snow for both image types. The precision values obtained from the k-means clustering method for the optical and thermal images were 0.69 and 0.91, respectively. The observed scores suggest that the model exhibited relatively lower precision when applied to optical images than when applied to thermal data. The findings suggest that the accuracy of k-means clustering in detecting instances of roadway snow coverage in optical data is relatively lower. The precision values obtained for the SVM model were 0.69 for the optical data and 0.87 for the thermal data. The observed values exhibit similarities to those of k-means clustering, further reinforcing the notion that SVM demonstrates lower precision when applied to optical data than when applied to thermal data.

The findings of this study indicated that the transfer learning model consistently demonstrates superior performance in terms of precision when compared to both the k-means clustering and SVM algorithms, specifically in the context of analyzing optical and thermal images. The performance of k-means clustering and SVM exhibited variations when applied to optical and thermal data. The results obtained from the team’s experiments indicated that k-means clustering exhibits a higher level of precision when applied to thermal data than when applied to optical data. The comparison between thermal and optical images highlighted their respective strengths and weaknesses.

Optical images provided superior results during the daytime, making them highly suitable for well-illuminated conditions. On the other hand, thermal images provided relatively better results during the nighttime, although the results were slightly worse than those provided by optical images during the day.

The study’s findings also shed light on the advantages of transfer learning in scenarios with limited training data. Even with a small dataset, the model demonstrated impressive performance, saving significant efforts in data collection and annotation. However, the trade-off between dataset size and training time should be carefully considered when scaling up the system.

The findings of this study indicate that the utilization of transfer learning and fine-tuning techniques on task-specific data results in improved accuracy in the detection of roadway snow.

RESULTS AND DISCUSSION

In this project, the researchers developed a multi-lane roadway snow coverage estimation framework composed of an automated data acquisition system, a computer vision process, a transfer learning algorithm, and evaluation metrics to understand system performance. The research team conducted field data collection with two dual-spectrum network cameras covering multiple lanes over two winter seasons. Image registration was first performed to align the infrared images with the optical ones for computational convenience.

Based on the team's observations through multiple snowstorms, optical images could generally support snow detection with sufficient illumination conditions. However, their performance degraded significantly at night or during snowstorms. On the other hand, infrared images could serve the same purpose with a sufficient temperature contrast but did not work well if the roadway surface reached thermal equilibrium. Therefore, the analysis of dual-spectrum images was necessary.

The researchers developed an image segmentation technique based on the 2D FFT feature vectors of a sliding window over an entire image. The k-means clustering method was applied to classify the feature vectors, and a mask was thereby generated for segmentation. SVM was also considered for image segmentation as a comparison. Moreover, the team performed the analysis for each lane individually by splitting a multi-lane FOV via segmentation and morphological operations. Subsequently, the snow coverage ratio of each lane was estimated using optical images during the daytime and infrared images at night. The time history of the snow coverage ratio was calculated. The researchers then evaluated performance by comparing segmentation results with the ground truth.

To handle the issue of a relatively limited data volume, the researchers harnessed the capabilities of transfer learning using the U-Net architecture implemented in the Keras framework. The system exhibited noteworthy performance in terms of precision across different image types. Specifically, it achieved a precision of 88% for daytime optical images and an impressive precision of 94% for nighttime thermal images, despite the constraints imposed by a limited dataset.

The achievement described in this report represents a noteworthy advancement in the automation of snow detection systems, which aims to enhance operational effectiveness and expediency in challenging meteorological circumstances, all while operating within the confines of a limited data volume.

The following conclusions were drawn based on the work conducted for this project:

- The developed data acquisition system and its optical and infrared images can be used for snow detection and roadway snow coverage estimation.

- With this specific data acquisition system, optical images are suitable for snow detection in sufficient illumination conditions, and infrared images outperform optical ones when illumination is low while temperature contrast is high.

- Since the developed computer vision method relies on textures in optical and infrared images, its performance is governed by contrasts provided by pixel intensity or temperature.

- The performance of image segmentation supported by k-means clustering was similar to the performance of image segmentation using SVM.

- The utilization of the transfer learning model proves to be particularly advantageous in scenarios where the acquisition of a substantial amount of labeled data presents challenges or requires a significant investment of time.

- The U-Net transfer learning model generally demonstrated superior or similar performance and efficacy when compared to k-means clustering and SVM.

While this study showcased the capability and performance of the proposed system and algorithms, the following limitations, lessons learned, and recommendations emerged for future researchers:

- The developed methodology was not tested for roadway ice detection due to the lack of evidence. Unlike for snow, the team did not have access to the ground truth from optical images, which do not provide indications of roadway ice, similar to the way our eyes cannot discern the presence of black ice. Therefore, data collection from test sites with different roadway conditions is recommended.

- Infrared camera performance in the daytime could be influenced by direct sunlight. Therefore, the effects of direct sunlight on the infrared camera lens need to be further investigated.

- Labeling optical and infrared images is critical to algorithm development. In this project, the researchers found that the manual labeling process is time-consuming and prone to errors. An efficient image labeling procedure needs to be considered for future studies.

- Integrating the methods developed in this research into a state DOT’s existing road monitoring systems could be challenging if the data collection camera is not compatible with local fiber optic networks. In this project, both cameras (with two different communication protocols) were supported by a local computer system rather than directly incorporated into local fiber optic networks. The application of the technology needs to be based on dual-spectrum or infrared cameras that are proven to be compatible with local fiber optic systems.

REFERENCES

Adams, M. 2005. *Pavement Temperature Sensors Project Summary*. Aurora Program, Iowa State University, Ames, IA.

Bhatia, Y., R. Rai, V. Gupta, N. Aggarwal, and A. Akula. 2022. Convolutional Neural Networks Based Potholes Detection Using Thermal Imaging. *Journal of King Saud University – Computer and Information Sciences*, Vol. 34, No. 3, pp. 578–588.

Aurora. 2005. *New Road Surface Condition Sensors*. Aurora Program, Iowa State University, Ames, IA.

Bai, X., M. Liu, and T. Wang. 2016. Feature Based Fuzzy Inference System for Segmentation of Low-Contrast Infrared Ship Images. *Applied Soft Computing*, Vol. 46, pp. 128–142.

Bhanu, B., S. Lee, and J. Ming. 1995. Adaptive Image Segmentation Using A Genetic Algorithm. *IEEE Transactions on Systems, Man, and Cybernetics*, Vol 25, No. 12, pp. 1543–1567.

Brewer, E., J. Lin, P. Kemper, J. Hennin, and D. Runfola. 2021. Predicting Road Quality Using High Resolution Satellite Imagery: A Transfer Learning Approach. *PLoS One*, Vol. 16, No. 7.

Bridge, P. 2008. Non-Invasive Road Weather Sensors. *4th National Conference on Surface Transportation Weather*, Indianapolis, IN.

Cheng, L., X. Zhang, and J. Shen. 2019. Road Surface Condition Classification Using Deep Learning. *J Vis Commun Image Represent*, Vol. 64.

Dahmane, K., P. Duthon, and F. Bernardin. 2018. Weather Classification with Traffic Surveillance Cameras. *Proceedings of the 25th ITS World Congress*.

Eom, T., Y. Kwon, and H. Ko. 2021. Compact Weather Sensor Node for Predicting Road Surface Temperature. *Sensors and Materials*, Vol. 33, No. 8, pp. 2763–2771.

Eriksson, M. and J. Norrman. 2001 Analysis of Station Locations in a Road Weather Information System. *Meteorological Applications*, Vol. 8, No. 4, pp. 437–448.

Ewan, L., A. Al-Kaisy, and D. Veneziano. 2013. Remote Sensing of Weather and Road Surface Conditions: Is Technology Mature for Reliable Intelligent Transportation Systems Applications? *Transportation Research Record: Journal of the Transportation Research Board*, No. 2329, pp. 8–16.

FHWA. 2023 *Road Weather Management Program*. https://ops.fhwa.dot.gov/weather/weather_events/snow_ice.htm.

Gonzalez, R. C. 2018. *Digital Image Processing*. Fourth edition. Pearson Education.

Jonsson, P. 2011. Remote Sensor for Winter Road Surface Status Detection. In *SENSORS, IEEE*, pp. 1285–1288.

Joshi, P. 2002. *A Mobile Road Condition Sensor as Winter Maintenance Aid*. Final Report for ITS-IDEA Project 85.

Karsisto, V. and L. Lovén. 2019. Verification of Road Surface Temperature Forecasts Assimilating Data from Mobile Sensors. *Weather and Forecasting*, Vol. 34, No. 3, pp. 539–558.

Khan, M. N. and M. M. Ahmed. 2019. Snow Detection using In-Vehicle Video Camera with Texture-Based Image Features Utilizing K-Nearest Neighbor, Support Vector Machine, and Random Forest, *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2673, No. 8, pp. 221–232.

Kubichek, R. F. and S. Yoakum-Stover. 1998. *Cost-Effective Microwave Sensing of Highway Road Conditions*. NCHRP IDEA 20-30/ IDEA 031. National Cooperative Highway Research Program, Washington, DC.

Kwon, T. 2002. *Final Report on Signal and Image Processing for Road Condition Classification.* AerotechTelub and Dalarna University under the Swedish National Road Agency, Stockholm, Sweden.

Kwon, T. J., L. Fu, and S. J. Melles. 2017. Location Optimization of Road Weather Information System (RWIS) Network Considering the Needs of Winter Road Maintenance and the Traveling Public. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 32, No. 1, pp. 57–71.

Landry, F. G. and M. A. Akhloufi. 2022. Deep Learning and Computer Vision Techniques for Estimating Snow Coverage on Roads using Surveillance Cameras. *18th IEEE International Conference on Advanced Video and Signal-Based Surveillance*.

Lei, Y., T. Emaru, A. A. Ravankar, Y. Kobayashi, and S. Wang. 2020. Semantic Image Segmentation on Snow Driving Scenarios. *2020 IEEE International Conference on Mechatronics and Automation (ICMA)*, pp. 1094–1100.

Li, L., F. Zhou, and X. Bai. 2018. Infrared Pedestrian Segmentation Through Background Likelihood and Object-Biased Saliency. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 19, No. 9, pp. 2826–2844.

Maarouf, A. A. and F. Hachouf. 2022. Transfer Learning-Based Ensemble Deep Learning for Road Cracks Detection. *ICAASE 2022 - 5th Edition of the International Conference on Advanced Aspects of Software Engineering*.

Mercelis, S., S. Watelet, and W. Casteels. 2020. Towards Detection of Road Weather Conditions Using Large-Scale Vehicle Fleets. *2020 IEEE 91st Vehicular Technology Conference*, pp. 1–7.

Misener, J. A. 1998. *Investigation of an Optical Method to Determine the Presence of Ice on Road Surfaces*. California PATH working paper.

Murphy, K. P. 2012. *Machine Learning: A Probabilistic Perspective*. MIT Press, Cambridge, MA.

Qian, Y., E. J. Almazan, and J. H. Elder. 2016. Evaluating Features and Classifiers for Road Weather Condition Analysis. *IEEE International Conference on Image Processing 2016*, pp. 4403–4407.

Roser, M. and F. Moosmann. 2008. Classification of Weather Situations on Single Color Images. *IEEE Intelligent Vehicles Symposium 2008*, pp. 798–803.

Ruiz-Llata, M., P. Martín-Mateos, J. R. López, and P. Acedo. 2014. Remote Optical Sensor for Real-Time Residual Salt Monitoring on Road Surfaces. *Sensors and Actuators B: Chemical*, Vol. 191, pp. 371–376.

Reed, J. and B. Barbour. 1997. *Remote Passive Road Ice Sensor System (RPRISS)*. IDEA Intelligent Transportation Systems Project final report, TRB IDEA ITS-34.

Saito, M. and S. Yamagata. 2014. *Effect of Video Camera-Based Remote Roadway Condition Monitoring on Snow Removal-Related Maintenance Operations.* Aurora Program, Iowa State University, Ames, IA.

Salehi, A. W., S. Khan, G. Gupta, B. I. Alabduallah, A. Almjally, H. Alsolai, T. Siddiqui, and A. Mellit. 2023. A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. *Sustainability*, Vol. 15, No. 7.

Schmokel, P. 2004. *Development of a Wide Area Optical Surface Contamination Detection System for Public Transportation Application*. Final report for Highway IDEA project 83. Cooperative Highway Research Program (NCHRP), Washington, DC.

Shapiro, L. G. and G. C. Stockman. 2001. *Computer Vision*. Vol. 3. Prentice Hall, New Jersey.

Solomon, C. and T. Breckon. 2011. *Fundamentals of Digital Image Processing: A Practical Approach with Examples in MATLAB*. John Wiley & Sons.

SRF Consulting Group, Inc. 2005. *Laboratory and Field Studies of Pavement Temperature Sensors*. Aurora Consortium, Iowa State University, Ames, IA.

Szeliski, R. 2010. *Computer Vision: Algorithms and Applications*. Springer Science & Business Media.

Vachmanus, S., A. A. Ravankar, T. Emaru, and Y. Kobayashi. 2021. Multi-Modal Sensor Fusion-Based Semantic Segmentation for Snow Driving Scenarios. *IEEE Sensors Journal*, Vol. 21, No. 15, pp. 16839–16851.

Ye, Z., X. Shi, C. K. Strong, and R. E. Larson. 2011. Vehicle-Based Sensor Technologies for Winter Highway Operations. *IET Intelligent Transport Systems*, Vol. 6, No. 3.

Zang, S., M. Ding, D. Smith, P. Tyler, T. Rakotoarivelo, and M. A. Kaafar. 2019. The Impact of Adverse Weather Conditions on Autonomous Vehicles: How Rain, Snow, Fog, and Hail Affect the Performance of a Self-Driving Cars. *IEEE Vehicular Technology*, Vol. 14, No. 2, pp. 103–111.

Zhao, J., H. Wu, and L. Chen. 2017. Road Surface State Recognition Based on SVM Optimization and Image Segmentation Processing. *Journal of Advanced Transportation*, Vol. 2017.

Zhuang, F., Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong, and Q. He. 2021. A Comprehensive Survey on Transfer Learning. *Proceedings of the IEEE*, Vol. 109, No. 1, pp. 43–76.

Zitova, B. and J. Flusser. 2003. Image Registration Methods: A Survey. *Image and Vision Computing*, Vol. 21, No. 11, pp. 977–1000.

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