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WINTER SAFETY IMPROVEMENT WITH COMPUTER VISION AND TRANSFER LEARNING

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16. Abstract

The preservation of road safety in snowy regions during the winter season is of paramount significance due to the presence of perilous meteorological circumstances, such as snowstorms, which can result in escalated vehicular collisions and subsequent roadway closure. In the present investigation, our primary objective is to devise a novel methodology aimed at tackling the aforementioned obstacle. This is achieved through the utilization of a hybridized system that incorporates both thermal and optical imagery to identify snow accumulation on road surfaces. By employing transfer learning techniques in conjunction with the U-Net architecture implemented in the Keras framework, our approach demonstrates notable efficacy in attaining precise outcomes, even when confronted with the limitations imposed by a restricted dataset. Our results demonstrate notable mean pixel accuracy (MPA) scores of 88% for roadway snow detection based on optical images captured during daytime and 94% based on thermal images acquired during nighttime. The encouraging results observed in this study underscore the potential of our dual-spectrum imaging technique to greatly improve road safety and reduce the number of collisions in winter conditions.

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Winter Safety Improvement with Computer Vision and Transfer Learning

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Disclaimer

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ABSTRACT

The preservation of road safety in snowy regions during the winter season is of paramount significance due to the presence of perilous meteorological circumstances, such as snowstorms, which can result in escalated vehicular collisions and subsequent roadway closure. In the present investigation, our primary objective is to devise a novel methodology aimed at tackling the aforementioned obstacle. This is achieved through the utilization of a hybridized system that incorporates both thermal and optical imagery to identify snow accumulation on road surfaces. By employing transfer learning techniques in conjunction with the U-Net architecture implemented in the Keras framework, our approach demonstrates notable efficacy in attaining precise outcomes, even when confronted with the limitations imposed by a restricted dataset. Our results demonstrate notable mean pixel accuracy (MPA) scores of 88% for roadway snow detection based on optical images captured during daytime and 94% based on thermal images acquired during nighttime. The encouraging results observed in this study underscore the potential of our dual-spectrum imaging technique to greatly improve road safety and reduce the number of collisions in winter conditions.

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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. 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. 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 an impressive precision of 94% when using dual-spectrum images. 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 with that of the computer vision algorithms.

1. INTRODUCTION

Slippery roadway conditions have posed high risks of vehicle collisions in snowy regions during winter seasons. Considering that friction coefficients of rubber tires on snow, compact snow, and ice surfaces are significantly lower than those of rubber tires on dry road surfaces, snowy and icy road conditions can lengthen vehicle braking distances and increase the risks of vehicle collisions. According to Federal Highway Administration (FHWA) safety statistics, vehicle crashes due to slippery (snowy or icy) road conditions lead to an annual average of 1,300 deaths and 116,800 injuries. Therefore, effective winter roadway maintenance is crucial to ensure traffic safety in snowy regions. Researchers have spearheaded a transformative shift in roadway condition analysis, employing cutting-edge image processing and machine learning (ML) techniques, with a primary focus on assessing slipperiness and weather patterns. These advancements capitalize on the immense potential of optical and thermal images, enabling a more comprehensive understanding of roadway slippery conditions. He et al. devised a groundbreaking methodology, integrating image processing techniques and ML algorithms, such as k-means clustering and support vector machines (SVMs), to evaluate multi-lane road slipperiness. By leveraging both optical and infrared images captured by a dual-spectrum camera, they achieved remarkable accuracy in identifying the snow-covered pixel percentage for each lane (1). Similarly, Landry et al. contributed to this field by estimating snow coverage using surveillance cameras and proposing a powerful ensemble ML model combining convolutional neural networks (CNN) and SVMs. The results of their study demonstrated superior accuracy compared with existing research (2). Aparna et al. approached the challenge of pothole detection with a commendable approach, collecting a diverse dataset of thermal images under various weather conditions. Through data augmentation techniques and leveraging a CNN model, they successfully identified potholes, addressing a critical aspect of roadway safety (3). To address the limitations of traditional image recognition technology for road recognition in intelligent driving systems, Cheng et al. proposed an innovative deep learning approach, which significantly enhanced the classification of road surface conditions, meeting the demand for rapid and accurate roadway condition monitoring (4).

ML approaches have found widespread use in infrastructure inspections, transforming the way we monitor and manage vital infrastructure assets. One of the primary benefits of ML in this domain is its capacity to process massive amounts of data from diverse sources, such as sensors, cameras, and historical records. ML models can assess these data in real time more precisely and effectively than traditional approaches, discovering defects, anomalies, and potential hazards. ML algorithms excel at predictive maintenance, allowing for the early detection of possible problems before they become costly breakdowns (5–7). ML-powered image identification and computer vision algorithms are critical in examining infrastructure components such as bridges, roads, and buildings (8). While the benefits of ML in infrastructure inspections are obvious, traditional ML 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 alternate methodologies such as transfer learning. Transfer learning approaches enable the application of knowledge from previously trained models on unrelated tasks to the specific infrastructure inspection task at hand. More recently, researchers intensified their focus on transfer learning as a means to augment the accuracy of roadway condition evaluations. 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 ML technique that enhances the performance of a model on a new, related task by leveraging knowledge gained from training on various 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, computational resources are constrained, or when aiming to achieve state-of-the-art performance across different domains (9) (10). One notable example of transfer learning's success in roadway condition assessment comes from Brewer et al. 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 U.S. model with Nigeria-specific data, they 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 (11). Additionally, Arya et al. demonstrated the versatility of transfer learning by training a comprehensive CNN model using roadway condition images taken by smartphones in Japan. They then fine-tuned this model for other countries by mixing the Japanese data with local data. This clever strategy allowed other countries to create their efficient models based on the pre-trained Japanese model. By doing so, they harnessed the power of transfer learning to optimize their model performance, even with limited local data (12).

The objective of this project is to improve the efficiency of automated roadway snow detection systems through the utilization of transfer learning methodologies, specifically in scenarios where data availability is constrained. The research endeavors to enhance the efficiency and precision of snow detection on road surfaces in winter conditions by leveraging a blend of optical and thermal images. This is achieved through the implementation of the U-Net architecture within the Keras framework, which facilitates the development of a novel approach. The present study aims 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 research outcomes could contribute to mitigating the risks of slippery roadway conditions and enhance winter roadway safety.

2. MATERIAL AND METHODS

This section presents a comprehensive overview of data collection, data pre-processing, and transfer learning model development.

2.1 Data Collection

Based on the expected precipitation and accessibility, the team identified two field test sites for data collection. The first site was located close to the I-80 Parleys Canyon RWIS station, Salt Lake City, Utah, as shown in Figure 2.1(a). Data collection was conducted using the compact thermal image streaming camera, FLIR A50, chosen for its exceptional features tailored to winter road conditions. The camera's notable attributes include a frame rate of 30 Hz, spectral range of 7.5–14.0 µm, fixed focus with adjustable options, and spatial resolution ranging from 1.2 to 4.0 mrad/pixel. With an infrared resolution of 464 × 348 pixels and visual resolution of 1,280 × 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 reading 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. The camera installation can be found in Figure 2.1(b). This data collection system operated continuously at the I-80 field site from November 2022 to April 2023 and November 2023 to April 2024, effectively capturing optical and infrared images through multiple winter storms characterized by significant roadway snow accumulation.

The second field site is located near the Park City RWIS station, Utah, as illustrated in Figure 2.1(c). We installed an InfiRay IRS-FB462A dual-spectrum bullet camera, with an operating temperature ranging from -40℃ to 70℃, to an extendable pole on the trailer via a customized fixture. Details of the dual-spectrum camera configuration and data acquisition system can be found in (1). A portable trailer continuously powered the data collection system with sets of batteries and solar panels, as shown in Figure 2.1(d). This system operated at the Park City field site from November 2023 to April 2024, during which three winter storms with significant accumulation of roadway snow were observed. These recorded images were regularly saved and transferred for further processing and analysis, providing a valuable winter road surface measurement dataset.

Figure 2.1 I-80 test site (a) location (1), and (b) camera installation. Park City test site (c) location, and (d) test setup with a portable trailer

2.2 Image Registration

This study involved the implementation of image registration techniques to achieve the alignment of thermal and optical images obtained from separate sensors. This alignment was crucial in order to facilitate enhanced data fusion and subsequent analysis of the acquired images. The process of image registration holds significant importance as it encompasses the spatial alignment of images from two lenses, thereby establishing pixel-to-pixel correspondence between them. In order to address spatial discrepancies that may arise from variations in lens locations and perspective angles, our objective was to achieve precise alignment of thermal and optical images. The team implemented the utilization of geometric transformation – the affine transformation model.

$$\begin{bmatrix} X' \\ Y' \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \qquad (1)$$

The coordinates *(X,Y)* correspond to a specific pixel in the thermal image, while the transformed coordinates *(X′,Y′)* correspond to the same pixel in the aligned optical image. The transformation is defined by the parameters *{a,b,c,d,e,f},* which represent the scaling, rotation, and translation components of the transformation. By implementing this registration methodology, it becomes possible to effectively integrate the thermal and optical data, thereby facilitating a thorough examination and augmenting the comprehension of the observed scene. Figures 2.2 and 2.3 illustrate the image registration process, showcasing the precise alignment of thermal and optical images from the I-80 eastbound lanes and the Park City test site using the affine transformation model represented in Equation 1. As shown in these two figures, the optical images are cropped and transformed to align with the thermal images. Considering the optical images have a higher resolution and wider field of view (FOV), they are registered for further analysis.

(a) (b) (c)

Figure 2.2 Example of image registration process involving (a) thermal image, (b) optical image, and (c) the corresponding registered image collected at the I-80 test site

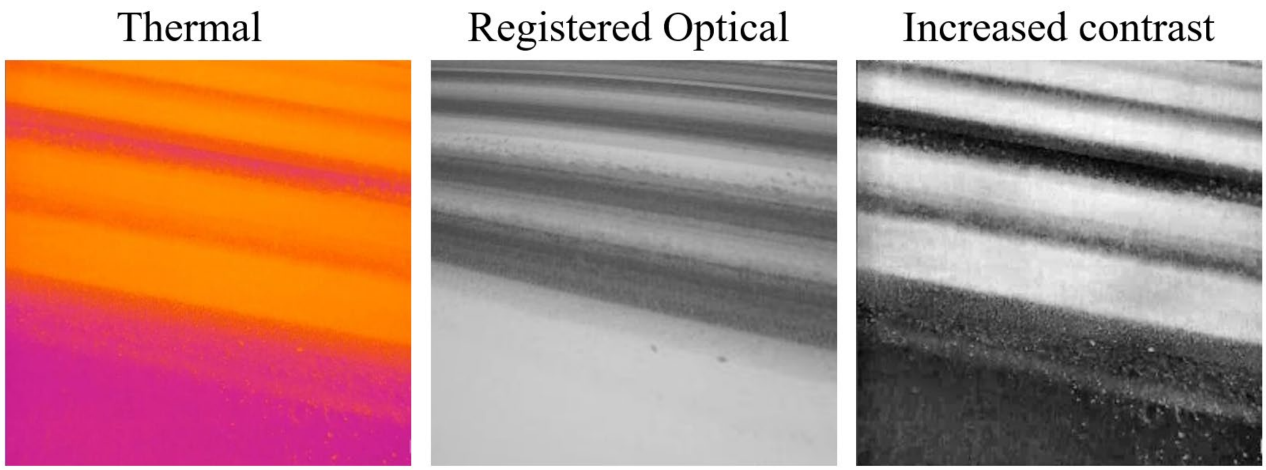

Figure 2.3 Example of image registration process involving optical thermal image, registered optical image, and the thermal image with enhanced contrast collected at the Park City test site

2.3 Transfer Learning

The transfer learning methodology was utilized in our study, where we employed the U-Net architecture within the Keras framework. Transfer learning enabled us to harness the capabilities of a pre-existing U-Net model, tailored explicitly for image segmentation, and customize it to suit our 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, we could 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 our specific task. In order to adapt the U-Net model to our particular application, we conducted fine-tuning of the final layers to acquire snow-specific features from our dataset. We also 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 our limited snow dataset. Figure 2.4 shows the transfer learning model architecture implemented for roadway snow detection.

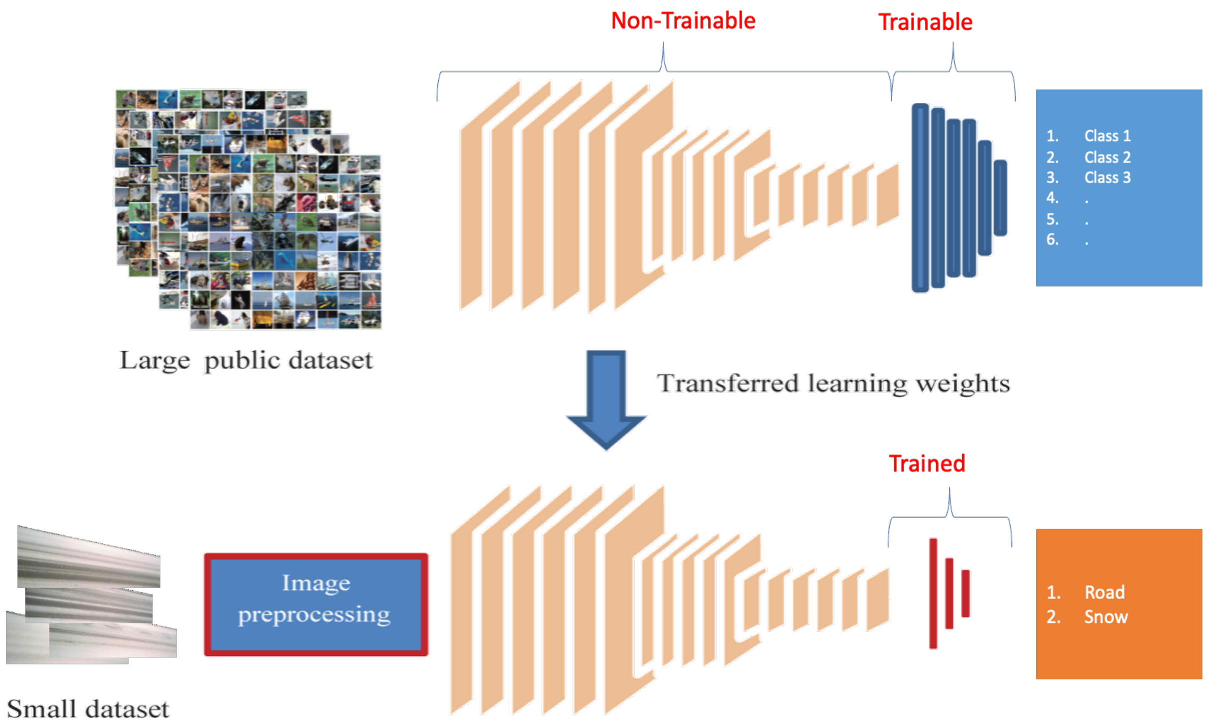

Figure 2.4 Transfer learning model architecture

We assessed the model's performance by using both quantitative and visual assessment techniques. We 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 our image segmentation task. In order to evaluate its performance in a quantitative manner, we calculated the categorical cross-entropy loss using a distinct test dataset. The model's ability to accurately segment objects in nighttime images improves as the loss decreases. We also computed the mean pixel accuracy (MPA) to assess the accuracy of segmentation. MPA represents the percentage of pixels that are classified correctly in comparison to the ground truth masks.

$$MPA = \frac{TP + TN}{TP + TN + FP + FN} \qquad (2)$$

where TP (true positives) is the number of pixels correctly classified as belonging to a particular class; TN (true negative) is the number of pixels correctly classified as not belonging to a particular class; FP (false positives) is defined as the number of pixels incorrectly classified as belonging to a particular class; and FN (false negatives) is the number of pixels incorrectly classified as not belonging to a particular class.

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

3. RESULTS AND DISCUSSION

The aim of our research study was to develop an efficient and accurate model for detecting snow-covered roads using both thermal and optical images. We 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 3.1 reveals that setting the trainable layers to five led to the highest MPA and the lowest test loss for both optical and thermal image-based models based on the data collected at the I-80 field site from November 2022 to April 2023 (during the first winter season). 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 performance with five trainable layers (the optimal layer design) is shown in Table 3.1.

Table 3.1 Performance of optimal transfer learning model (with five trainable layers) based on the data collected during the first winter season.

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

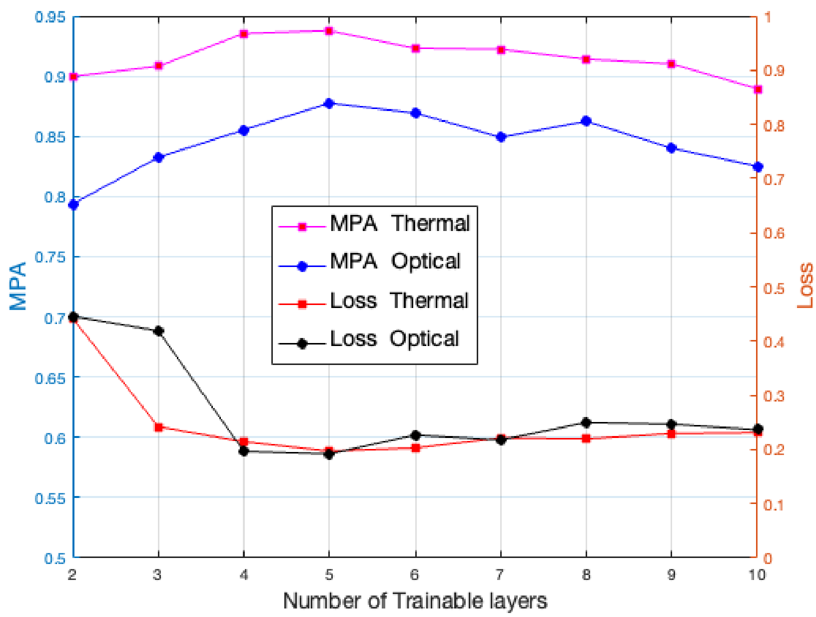

Figure 3.1 Assessing the model performance using various trainable layers and datasets, including both optical and thermal images, collected from the I-80 field site from November 2022 to April 2023

The model's performance was assessed concerning the imaging modality used – thermal and optical images. Optical images display superior results during daytime due to their higher resolution and ample illumination. In contrast, the performance of the model with thermal images was slightly impacted during 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 the model performance. Surprisingly, Figure 3.2(a) indicates the model exhibited excellent performance even with a very small dataset. As the dataset size is increased from 10 to 64 images, no significant improvement in the model's performance is observed. This finding emphasizes 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, there was a noticeable trade-off in terms of training time. Figure 3.2(b) demonstrates the time required for model training escalates significantly as the number of trainable layers increases. Researchers and practitioners must consider this trade-off when deploying the system, as larger datasets may demand more computational resources and time for training.

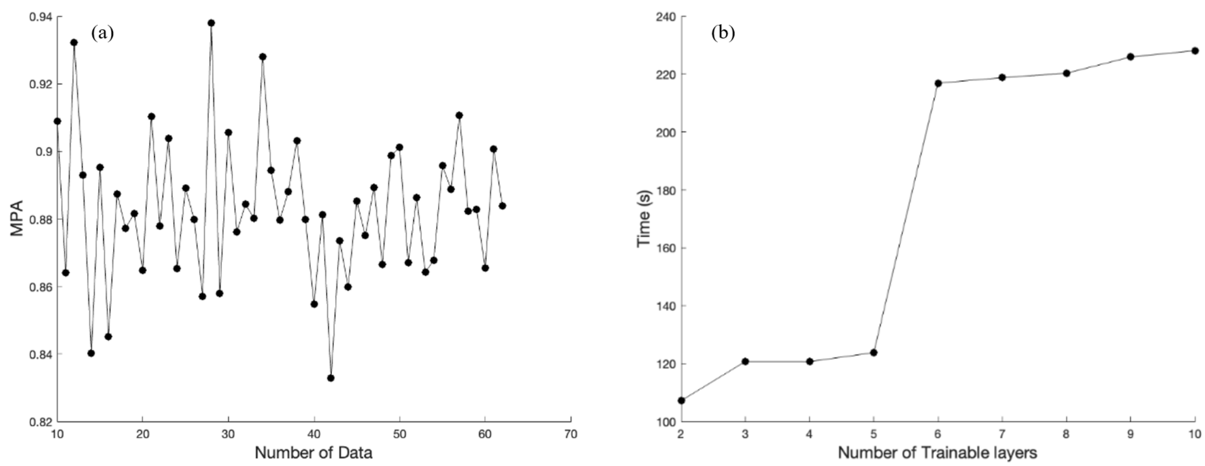

Figure 3.2 Parametric study: (a) performance evaluation with various number of data; (b) the relationship between the training time and number of trainable layers based on the data collected from the first winter season

The results of our study demonstrate the successful utilization of thermal and optical images for snow detection on roads. By employing transfer learning, we achieved efficient and accurate results, making the approach suitable for real-time applications. Controlling the number of trainable layers proved to be essential in optimizing the model performance as it influenced the complexity and generalization capabilities. Table 3.2 evaluates the precision of different ML models for the task of roadway snow detection. Precision is a metric used to measure the proportion of true positive predictions among all positive predictions made by the model. In this context, it indicates how accurate the models are in identifying instances of roadway snow using optical and thermal images.

Table 3.2 Evaluating the performance of three distinct machine learning approaches for detecting roadway snow based on data collected from the US 89 test site during the first winter season

MPA (Precision)	Optical	Thermal
Transfer learning model	0.94	0.88
K-means clustering (*1*)	0.69	0.91
Support vector machines (*1*)	0.69	0.87

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 obtained high precision scores indicate that the model exhibits a commendable level of effectiveness in accurately detecting instances of roadway snow for both image types. The precision values obtained from the k-means model for the optical and thermal images are 0.69 and 0.91, respectively. The observed scores suggest that the model exhibits a relatively lower precision when applied to optical images in comparison with thermal data. The findings suggest that the accuracy of k-means clustering in detecting instances of roadway snow-coverage in the optical data is relatively lower. The precision values obtained for the SVM model are 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 SVMs demonstrate lower precision in the context of optical data when compared with thermal data.

The findings of this study indicate that the transfer learning model consistently demonstrates superior performance in terms of precision when compared to both k-means clustering and SVM algorithms, specifically in the context of analyzing optical and thermal images. The performance of k-means clustering and support vector machines exhibits variations when applied to optical and thermal data. The results obtained from our experiments indicate that k-means clustering exhibits a higher level of precision when applied to thermal data as opposed to optical data. Conversely, SVMs demonstrate comparable performance on both types of data. 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.

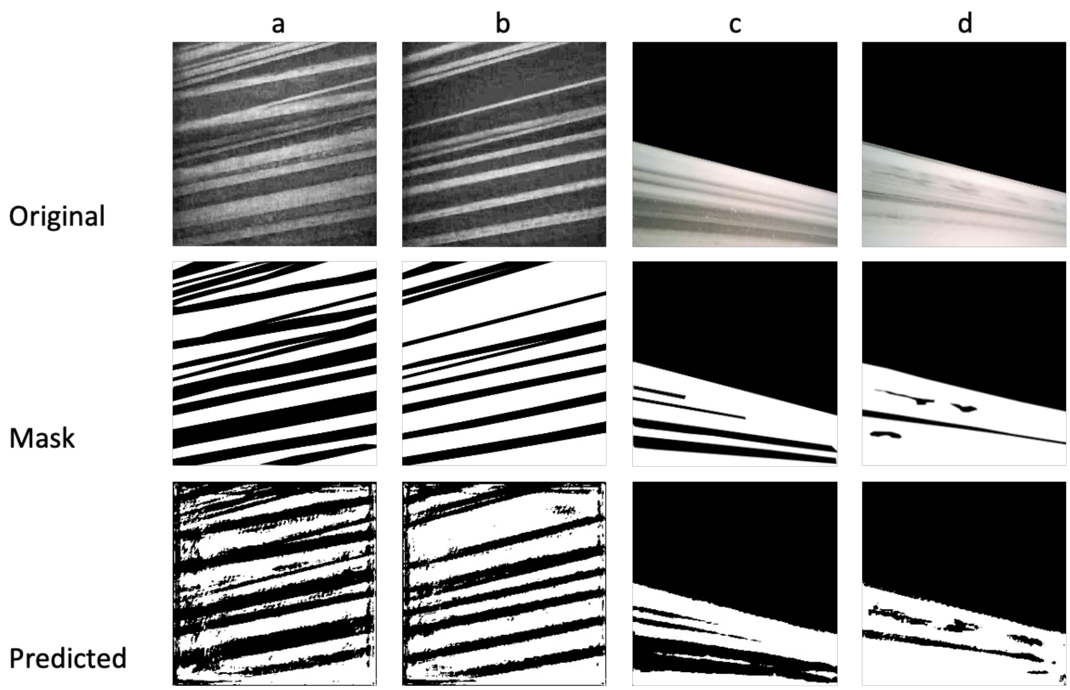

Figure 3.3 Model predications alongside the mask (ground truth) and original images.(a) and (b): examples of thermal images recorded at nighttime from the US 89 test site; (c) and (d): examples of optical images captured during daytime from the I-80 test site.

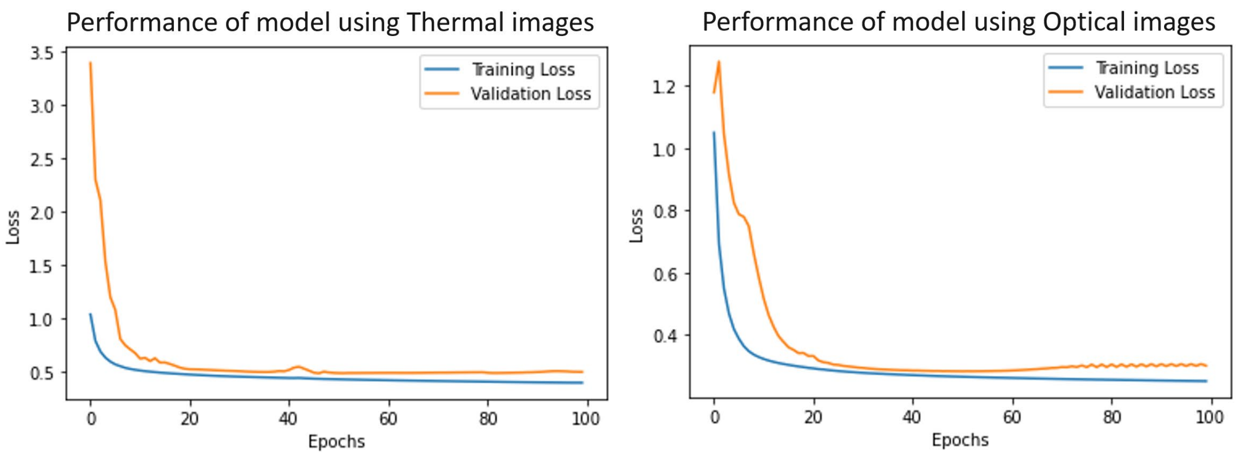

Figure 3.4 Training and validation losses using thermal images (left) and optical images (right) based on data collected during daytime from the I-80 and Park City test sites in the second winter season.

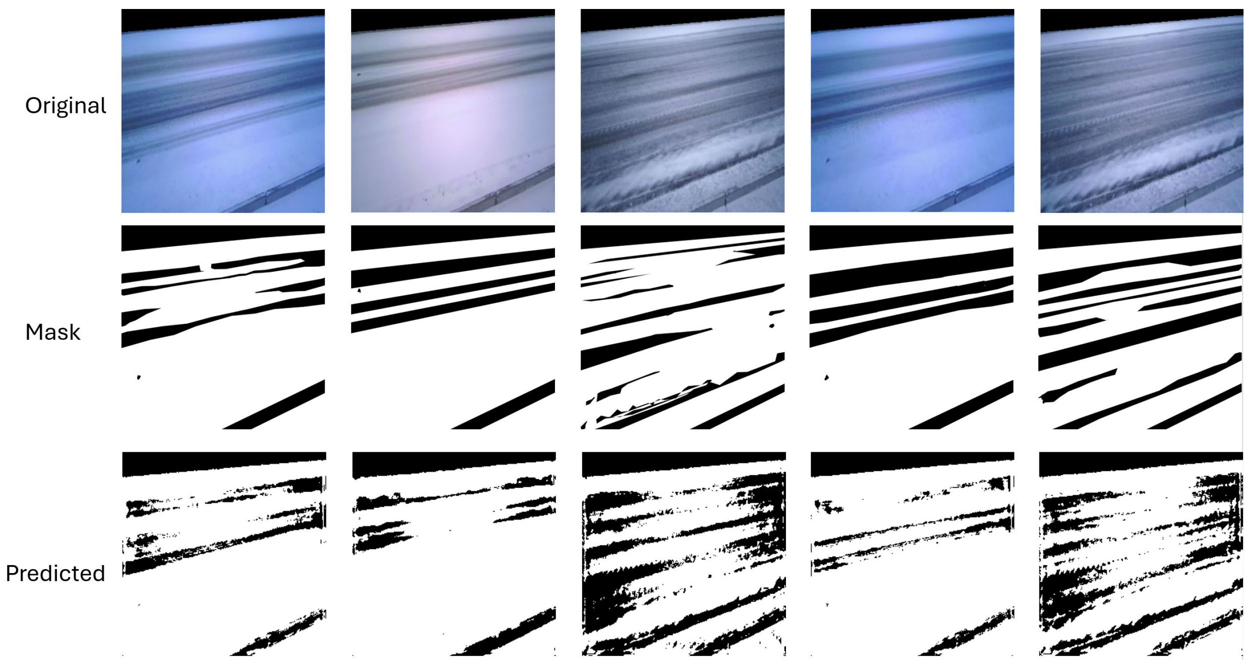

Figure 3.5 Model predications alongside the mask (ground truth) and original images based on optical images captured during daytime from the I-80 test site during the second winter season

The comparison between thermal and optical images highlighted their respective strengths and weaknesses. Optical images provided superior results during daytime, making them highly suitable for well-illuminated conditions. On the other hand, the thermal image-based model performance was relatively better during nighttime, though slightly lower compared with 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. Examples of using the optical images collected from the first winter season are shown in Figure 3.3. Satisfactory performance of the transfer learning models based on data collected during the second winter season is shown in Figures 3.4 and 3.5.

4. CONCLUSIONS

This report effectively examined the identification of snow-covered roadways by employing a novel amalgamation of thermal and optical imagery. By harnessing the capabilities of transfer learning using the U-Net architecture implemented in the Keras framework, our research has yielded encouraging outcomes. The system exhibited noteworthy performance in terms of MPA across different image types. Specifically, it achieved an MPA of 88% for daytime optical images and an impressive 94% for nighttime thermal images, despite the constraints imposed by a limited dataset. The achievement described herein represents a noteworthy advancement in the automation of snow detection systems, which aim to enhance operational effectiveness and expediency in challenging meteorological circumstances, all while operating within the confines of limited data volume.

Through the utilization of transfer learning, our methodology demonstrated its capacity to enhance the efficacy of automated snow detection systems, all while circumventing the need for an extensive dataset. The utilization of this approach proved to be particularly advantageous in scenarios where the acquisition of a substantial amount of labeled data presents challenges or requires a significant time investment. The demonstrated efficacy of the U-Net architecture in the context of snow detection on roads highlights its suitability for this particular task, thereby establishing its significance as a valuable instrument for both future investigations and practical implementations. Furthermore, the attainment of elevated MPA for both optical and thermal images verifies the adaptability and resilience of our approach, enabling it to operate efficiently under diverse lighting and meteorological circumstances.

Based on our research, the obtained results present promising prospects for the improvement of road safety and transportation in adverse weather conditions. The enhanced velocity and efficacy of our automated snow detection system holds the potential to assist governing bodies in formulating well-informed judgments and executing prompt measures to alleviate perilous road conditions. As the progression of technology persists, our investigation establishes the fundamental basis for subsequent enhancement and streamlining of snow detection systems. These systems hold the potential to be seamlessly integrated into intelligent transportation systems, thereby augmenting winter roadway safety in snowy regions.

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