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Decision Support for Snow Removal Dispatch Integrating Meteorological Information and Fixed-camera Images

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Snow removal dispatch decisions during winter nights require not only the accurate prediction of dispatch necessity but also the intuitive presentation of road conditions and decision-relevant information to human operators. In this study, we propose a snow removal dispatch decision support method that integrates fixed-camera images and meteorological information to both predict dispatch necessity and visualize information for operational support. The proposed method employs a machine learning model with feature selection, integrating meteorological observations, short-term forecasts, snow depth measurements, and an image-derived road condition indicator called the snow coverage ratio (*SCR*). From a sensing perspective, the proposed method integrates heterogeneous environmental sensing modalities—including fixed-camera imaging, snow-depth sensing, and meteorological sensing—to represent road surface conditions relevant to dispatch decision-making. By visualizing road conditions together with prediction results, the system provides operators with objective and consistent situational awareness to support decision-making. Experimental results confirm that *SCR* effectively reflects temporal changes in road conditions and contributes to dispatch prediction. Furthermore, evaluation using data collected under similar winter meteorological conditions shows that a dispatch prediction model with L1 regularization tends to outperform human operators' decisions. Additional evaluation applying models trained on past-year data to subsequent years demonstrates that training with multi-year datasets improves generalization under varying winter conditions. These results indicate that the proposed method provides practical and reliable support for snow removal dispatch decisions in real operational environments.

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1. Introduction

Ensuring safe road traffic during winter in heavy snowfall regions requires timely and appropriate snow removal operations. However, dispatch decisions for snow removal involve highly complex judgments that depend on rapidly changing meteorological and road surface conditions, forcing operators to make decisions under considerable uncertainty. In particular, during fresh-snow removal conducted at night, decisions made within a work shift are often overturned only a few hours later. This leads to uncertain standby burdens on snow removal workers and psychological stress on decision makers. Moreover, nighttime patrols conducted to supplement decision-making are not desirable owing to accident risks associated with vehicle travel and the additional manpower required.

Traditionally, dispatch decisions in snow removal operations have relied on the experience of on-site personnel and partial information extracted from weather forecasts. Although advances in meteorological observation and imaging technologies have enabled the acquisition of detailed road and environmental information, no framework has been established to integrate such heterogeneous data in a manner that directly supports dispatch decision-making. In particular, no existing system has realized the real-time collection of road surface images from fixed cameras, short-term meteorological forecasts, and snow depth measurements, and combined these data with predictive functionality for operational decision support.

In this study, sensing technologies play a central role in representing road surface and environmental conditions relevant to snow-removal dispatch decisions. Fixed roadside cameras function as optical sensors that continuously capture spatially distributed road images, snow-depth sensors provide quantitative measurements of accumulated snow at representative locations, and meteorological sensing systems (e.g., precipitation gauges, thermometers, and anemometers) supply continuous observations of weather conditions. These heterogeneous sensing modalities enable both spatially detailed and quantitatively grounded observations of winter road environments. The proposed system integrates these sensor-derived observations—including image-based snow coverage ratio (SCR), snow depth, and meteorological measurements—to construct a unified sensing-based representation of road surface conditions for decision support.

To address these challenges, we developed an integrated system for supporting snow removal dispatch decisions. The system automatically collects and organizes network camera images, meteorological forecast data, and snow depth information from multiple locations, providing an environment in which operators can efficiently and promptly grasp the current situation. In addition, the system provides the unified visualization of heterogeneous data—including road images, weather forecasts, and snow depth measurements—on a single screen. This reduces the fragmentation of necessary information and eases the cognitive burden associated with situation assessment, particularly during late-night operations. This integrated visualization represents a secondary contribution of this study.

Furthermore, to estimate the necessity of future dispatch, we incorporate a machine-learning-based prediction model that supplements and enhances conventional experience-dependent decision-making. Although meteorological information contains a wide variety of quantitative and qualitative attributes, only a limited subset has been utilized in previous systems. In this study, we employ an L1-regularized feature selection approach to automatically extract effective predictive factors from a large pool of candidates, enabling the efficient utilization of diverse meteorological information, including categorical variables such as weather codes and wind directions.

The primary contributions of this study are summarized as follows:

1. We construct a snow removal dispatch support system that integrates road surface images, meteorological forecasts, and snow depth data, and incorporates a predictive model for operational decision-making.
2. We introduce an L1-regularized feature selection method that automatically extracts effective features from diverse meteorological information.
3. We conduct an initial evaluation assuming real-world deployment and confirm the practical utility of the proposed system.

The proposed system is expected to improve the objectivity of dispatch decisions, reduce the risk of overlooked operational needs, and alleviate the psychological burden on both decision makers and snow removal workers. This study provides practical insights into the integrated use of sensing technologies and AI-based decision support for winter road maintenance.

Although previous studies have addressed partial aspects related to snow removal operations—such as road surface estimation, wide-area winter maintenance planning, and demand forecasting for weather-sensitive public services—these approaches have typically remained independent of one another. In particular, no existing framework has systematically integrated heterogeneous data sources, including road images, meteorological information, and snow depth measurements, and linked them with a predictive model to support dispatch decision-making. To clarify the position of this study, in the next section, we review related work in a structured manner and identify the research gaps that the present study aims to address.

2. Data, Materials, and Methods

In this section, we outline four major research areas related to the snowplow dispatch decision support system targeted in this study. These areas are the following: (1) winter road management and snow removal support, (2) road surface condition estimation using weather and camera data, (3) public service demand forecasting for urban infrastructure operations, and (4) feature selection and interpretability in machine learning. By reviewing representative works in each domain, we clarify the positioning and originality of our research.

2.1 Winter road management and snow removal support

Ensuring road safety in winter is a critical issue, and various decision support systems (DSSs) have been developed to aid snow removal operations. The Maintenance Decision Support System developed by the U.S. Federal Highway Administration in the early 2000s combined detailed weather forecasting with rule-based decision logic to recommend treatment strategies for each road segment.[1] With the advancement of AI and IoT technologies, there is a growing demand for more real-time and accurate decision support. For example, Khan and Ahmed[2] proposed a deep-learning-based method for road condition monitoring using camera images, demonstrating the effectiveness of combining sensor data and imagery. In addition, Feng and Fu[3] developed a road surface condition prediction method based on a heat balance model to support winter road management operations.

2.2 Road surface and risk estimation using weather and camera data

The accurate understanding of road surface conditions is directly linked to the early detection of slipperiness and accident risk. Jonsson[4] classified road surface conditions using Road Weather Information System data and camera images. Recently, deep-learning-based methods have achieved high precision; Du *et al.*[5] improved the classification accuracy of road surface conditions using convolutional neural networks. Furthermore, Zhang *et al.*[6] proposed a method based on convolutional neural networks integrating visible and thermal images for winter road surface classification. In addition, Tabrizi *et al.*[7] developed a deep learning model to forecast road surface temperature, which is closely related to freezing risk, demonstrating the potential for proactive measures.

2.3 Public service demand forecasting and urban infrastructure management

Decision-making for snowplow dispatch shares similarities with public service demand forecasting. Monks *et al.*[8] developed a forecasting model for daily ambulance demand and demonstrated its application to operational planning based on temporal variability. Furthermore, Miyatake *et al.*[9] analyzed the relationship between heatstroke-related ambulance transports and meteorological variables, showing that temperature significantly affects emergency transport demand. In addition, Tarcea *et al.*[10] proposed a weather-based index to predict slip- and fall-related injuries under icy conditions, highlighting the importance of environmental factors in risk estimation. Internationally, previous studies have achieved highly accurate forecasts of ambulance demand using spatio-temporal modeling and machine learning approaches.[11,12]

2.4 Feature selection and interpretable machine learning

In applying AI to safety and public domains, not only model accuracy but also transparency and interpretability are critical. Chandrashekar and Sahin[13] conducted a comprehensive survey on feature selection methods, emphasizing that removing redundant variables can simplify models while improving interpretability. The least absolute shrinkage and selection operator (LASSO), proposed by Tibshirani,[14] is a representative method for constructing sparse models by automatically selecting only important features. Local explanation techniques for black-box models such as LIME by Ribeiro *et al.*[15] and SHAP by Lundberg and Lee[16] enable the validation of decision-making rationale. Rudin[17] advocated for directly designing interpretable models, arguing that such approaches are particularly necessary in safety-critical applications.

2.5 Positioning and contributions of this research

On the basis of the aforementioned studies, we constructed a snowplow dispatch DSS that integrates sensor data, image analysis, and machine learning. Unlike previous studies, our system enables the estimation of *SCR* from fixed-camera images, dispatch prediction using weather and infrastructure data, interpretable forecasting models incorporating LASSO-based feature selection, and a user interface that visualizes heterogeneous data types on a single screen. These features collectively support on-site decision-making while reducing cognitive load, enabling decision support that balances real-time responsiveness, predictive accuracy, and usability.

3. Snow Removal Operations and the Current Dispatch Decision Process

In this section, we outline the snow removal operations and decision-making practices in the target region. We begin by describing the operational and psychological challenges associated with late-night dispatch decisions, followed by an examination of the limitations of current visualization-oriented support systems. We conclude this section by summarizing these issues and clarifying the technical requirements that motivate the development of the proposed method presented in Sect. 4.

3.1 Operational challenges in night-time dispatch

In municipalities located in heavy-snowfall regions, snow removal operations are implemented as a public safety service to maintain road trafficability and ensure the safety of residents. Dispatch decisions must consider multiple factors, including snowfall intensity, accumulated snow depth, the time required to mobilize workers, and the need to complete road treatment before the morning peak traffic period.

In this study, we focused on the Rumoi and Horonuka regions in northwestern Hokkaido, Japan, located along the Sea of Japan. This coastal area is characterized by heavy snowfall, strong winter winds, and frequent snowdrift formation, which cause rapid and substantial changes in road surface conditions. The target road network consists of urban national roads in Rumoi, suburban national roads in Horonuka, and a high-standard highway segment, each exhibiting distinct traffic conditions and snow-accumulation patterns. These regional characteristics make dispatch decision-making especially challenging, particularly during late-night hours.

Among all snow removal operations, late-night snowfall (00:00–06:00) poses the greatest difficulty for decision makers. The primary reasons are as follows:

(1) Reduced observability: Road conditions are harder to monitor at night owing to darkness and limited patrol coverage.

(2) High uncertainty: Meteorological conditions such as snowfall intensity, wind speed, and wind direction can change considerably within a short period.

(3) Increased standby burden: Because initial decisions may later be reversed, workers often remain on extended standby without certainty of dispatch.

(4) Psychological pressure: Incorrect decisions can lead to hazardous road conditions during the morning traffic period, increasing accident risks.

In practice, it is common for an early-night decision to be overturned later, requiring sudden crew mobilization under severe time constraints. To compensate for this uncertainty, supervisors sometimes perform night-time patrols to visually inspect road surface conditions. However, patrol driving under poor visibility entails safety risks and imposes a substantial manpower burden. These issues indicate that late-night dispatch decisions require rapid situational assessment under high uncertainty, resulting in significant operational and psychological load on personnel.

3.2 Limitations of conventional visualization-oriented support systems

With advancements in sensing and information technologies, many municipalities now collect road surface images, snow depth measurements, and short-term meteorological forecasts across multiple observation points. Existing systems typically provide real-time fixed-point camera images, snow depth and precipitation measurements, and short- and medium-term weather forecast parameters.

However, the primary function of such systems remains visualization, requiring operators to interpret heterogeneous information sources individually and make decisions largely on the basis of experience. As a result, conventional systems exhibit several major limitations:

1. Fragmented information sources and increased cognitive load
   Road images, weather forecasts, and snow depth data are often presented separately, requiring the manual integration of multiple information streams to form a situational understanding. This fragmentation is particularly problematic during late-night operations, when timely decision-making is crucial. Although Sects. 1 and 2 introduced an integrated visualization environment, typical systems lack such capabilities.
2. Absence of quantitative interpretation of road images
   While fixed-point cameras provide visual information, they do not offer quantitative measures such as the proportion of the road surface covered by snow and the spatial extent of snow accumulation. Consequently, decisions often depend on subjective interpretation.
3. Limited utilization of available meteorological attributes
   Meteorological datasets include diverse quantitative and qualitative variables—temperature, precipitation, wind direction, and weather codes—but dispatch decisions commonly rely on only a subset of these attributes, leaving potentially informative features underutilized.
4. Lack of predictive support functionality
   Conventional systems present past and present conditions but do not estimate future dispatch necessity.

As a result, decision-making remains highly dependent on operator experience, making objective and reproducible judgments difficult to achieve.

3.3 Motivation for the proposed framework

Although the volume of available information has increased, existing systems do not provide the integrated understanding of heterogeneous sensing data nor the predictive insights essential for reliable dispatch decision-making. These limitations are particularly critical in regions such as Rumoi and Horonuka, where weather conditions change rapidly and late-night decisions carry high operational and psychological burden. Accordingly, a next-generation decision support framework must satisfy the following requirements: the integration of heterogeneous sensing data—including road images, meteorological forecasts, and snow depth measurements—on a unified platform; the quantitative analysis of road surface conditions, enabling objective assessment beyond visual inspection; the extraction of effective predictive features through appropriate feature-selection techniques; and a predictive model capable of estimating dispatch necessity in an interpretable and reproducible manner.

To address these requirements, we developed a snow removal dispatch support system that combines integrated visualization, quantitative image analysis, L1-based feature selection, and a machine learning dispatch prediction model. In Sect. 4, we introduce the architecture of this system and explain each component of the proposed method in detail.

4. Proposed Method

In this section, on the basis of the challenges and requirements identified in the previous section, we describe the overall design of the snow removal dispatch support system developed in this study. The proposed method consists of the following four core components:

1. Integrated visualization of heterogeneous sensor data
   Road surface images, snow depth data, and weather forecasts—previously referred to individually—are centralized into a unified interface to accelerate situational awareness.
2. Quantitative estimation of snow coverage using image analysis
   Fixed-point camera images are processed to estimate *SCR*, converting subjective visual judgment into a numerical indicator.
3. Feature selection using L1 regularization
   Effective features contributing to dispatch decisions are automatically selected from meteorological and image-derived information to improve model interpretability and generalization.
4. Machine-learning-based dispatch necessity prediction
   The extracted features are used to probabilistically estimate the necessity of nighttime dispatch, enhancing the objectivity and reproducibility of decision-making.

These components directly address the issues identified in Sect. 3: fragmented information sources, the nonquantitative interpretation of images, the underutilization of meteorological attributes, and the lack of predictive functionality. The following sections describe the system architecture and the technical details of each component.

4.1 System architecture

In this section, we outline the system architecture used to automatically acquire and integrate heterogeneous data, including fixed-point camera images, meteorological observations, weather forecasts, and snow depth measurements. Because these data differ in sampling frequency and format, appropriate preprocessing and temporal alignment are applied to ensure consistency for subsequent image analysis, feature engineering, and dispatch prediction.

The meteorological information integrated in this system consists of two categories: meteorological observations (e.g., temperature, wind speed, wind direction, relative humidity, precipitation, and atmospheric pressure) and short-term weather forecasts. Observations represent current environmental conditions, while forecasts are essential for anticipating near-future snowfall and temperature decreases. Aligning these heterogeneous data streams on a unified timeline provides a foundation for both situational assessment and predictive decision support.

The system comprises four components: a data acquisition module, a preprocessing module, an integrated data management module, and an information-sharing website. The data acquisition module periodically collects fixed-point camera images and automatically retrieves meteorological observations and forecasts via Web APIs. Snow depth data are collected similarly, and unified timestamps are assigned to all data.

Camera information and roadside snow depth sensor data were limited to the 6:00–16:00 period to ensure reliable road surface observation conditions. *SCR* estimation from images requires sufficient daylight visibility, whereas nighttime images are affected by low illumination, headlight glare, and snowfall reflections that degrade segmentation accuracy. Snow depth sensor measurements at roadside locations may also be affected by shadowing and increased noise under nighttime conditions. In contrast, meteorological observations are independent of illumination and remain reliable over 24 h; therefore, nighttime weather data were included.

The snow accumulation information used in the system represents snow depth derived from meteorological observations or point-based measurements, which indicate overall snowfall conditions over relatively wide areas or limited sensor locations. In contrast, *SCR* estimated from camera images provides spatially continuous information on actual snow coverage on the monitored road surface. While snow depth reflects snowfall intensity, *SCR* directly captures road surface snow coverage relevant to dispatch decisions. Therefore, *SCR* complements snow depth by providing localized and road-specific condition information that cannot be obtained from meteorological or point-based measurements alone.

The preprocessing module performs missing-value imputation, outlier removal, unit conversion, and temporal alignment between observations and forecasts to ensure the data quality required for machine learning models. Temporal alignment is particularly important for matching differing update intervals across data sources.

The integrated data management module stores all preprocessed data and enables unified reference to images, meteorological information, and snow depth values at any given time. This eliminates the need for operators to manually reconcile multiple sources during nighttime decision-making.

An overview of the data flow and processing pipeline is shown in Fig. 1. As illustrated, the system forms a continuous processing chain from data acquisition to preprocessing, feature engineering, and dispatch prediction, with each technique described in Sects. 4.2–4.4.

To support field operations, an information-sharing website has been developed to allow efficient access to integrated data. The website automatically displays synchronized camera images, meteorological observations, short-term forecasts, and snow depth data across multiple locations. A sample screen is shown in Fig. 2. This platform enables operators to quickly evaluate road and weather conditions, and reduces the workload associated with nighttime patrols.

The information-sharing website displays synchronized fixed-point camera images, meteorological observations, short-term forecasts, and snow depth data across multiple locations. In addition, dispatch necessity prediction results for each route/location are displayed at the top of the interface, enabling operators to simultaneously assess current road conditions and predicted dispatch requirements.

Figure 3 illustrates the operator workflow at the 16:00 dispatch planning stage before and after the introduction of the proposed system. The overall decision sequence remains unchanged, consisting of situation check, information review, and dispatch decision. Prior to system introduction, operators viewed distributed information sources such as meteorological data, camera images, and patrol reports, and manually integrated them. With the proposed system, this step is replaced by accessing a unified information-sharing site that integrates meteorology, camera data, *SCR* visualization, and prediction outputs, enabling centralized situational assessment prior to dispatch decision and reducing information access burden.

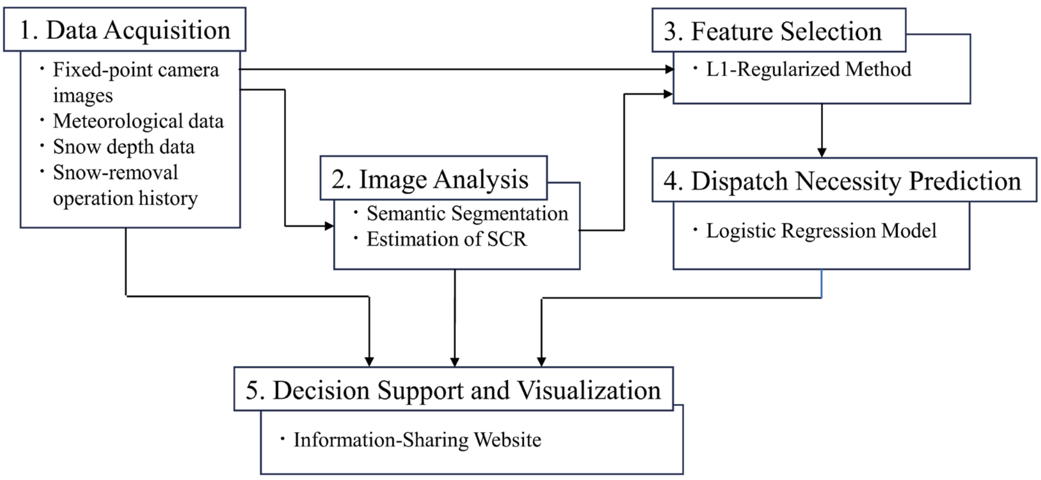


Fig. 1. Overview of the system architecture and data-processing flow. The system integrates heterogeneous data sources, including fixed-point camera images, meteorological observations and forecasts, snow depth data, and operation history. Image analysis estimates *SCR* via semantic segmentation. Feature integration and L1-regularized feature selection are applied to construct an effective input set for the dispatch prediction model. A logistic regression model outputs the probability of dispatch necessity, which is then visualized through an information-sharing website for decision support.

Fig. 2. (Color online) Sample screen of the snow removal information-sharing website. The website displays synchronized fixed-point camera images, meteorological observations, short-term weather forecasts, snow depth information, and dispatch necessity prediction results for each route/location collected from multiple locations. This integrated view enables operators to quickly assess road and weather conditions, and reduces the workload associated with nighttime monitoring.

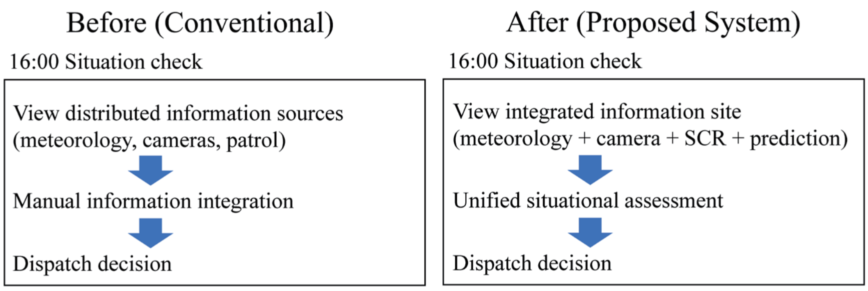


Fig. 3. (Color online) Comparison of operator tasks in the 16:00 dispatch planning workflow before and after introduction of the proposed information-sharing system. While the decision sequence remains unchanged (situation check → information review → dispatch decision), viewing distributed information sources (meteorology, cameras, and patrol reports) is replaced by accessing an integrated information-sharing site that unifies meteorological data, camera images, *SCR* visualization, and prediction outputs, enabling centralized situational assessment.

4.2 Quantification of snow coverage via semantic segmentation

In this section, we explain how snow coverage is quantified using semantic segmentation applied to fixed-point camera images. Following the approach of Okura *et al.*,[18] the road surface in each image is classified into the following four classes: snow, non-snow, obstacle (e.g., vehicles, buildings, guardrails, and poles), and irrelevant sky and distant background regions.

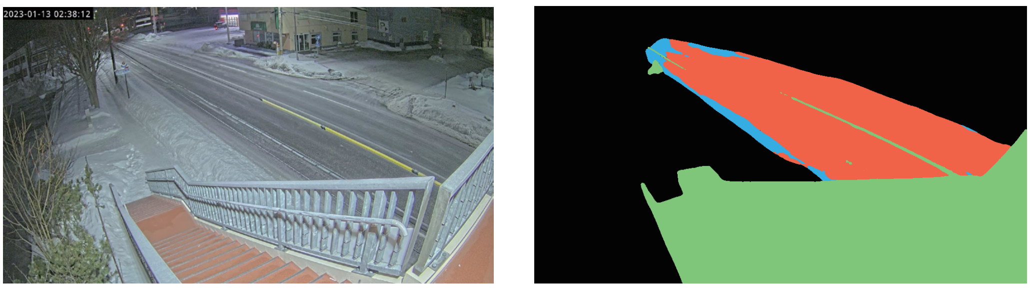
An example of the segmentation result is shown in Fig. 4. The left image (before) shows the original camera input, where snow visibility may be affected by illumination and surface reflections. The right image (after) shows the segmentation output, where the three classes are distinctly identified, allowing the snow-covered region to be extracted. To quantify the degree of snow coverage, obstacle regions are excluded, and *SCR* is defined using the number of snow and non-snow pixels:

$$SCR = N_{snow} / (N_{snow} + N_{nonsnow}), \tag{1}$$

where N_{snow} is the number of snow pixels and $N_{nonsnow}$ is the number of non-snow pixels. This definition captures the proportion of snow-covered areas on the visible road surface, enabling the quantitative tracking of road condition transitions such as snowfall onset, accumulation, and melting. *SCR* serves as an important explanatory feature in the dispatch prediction model described later.

4.3 Feature selection using L1 regularization

In this section, we describe the selection of effective features from meteorological information, snow depth data, and image-derived indicators such as *SCR*. We employ logistic regression with L1 regularization (LASSO) for feature selection. L1 regularization induces sparsity in the model coefficients by shrinking irrelevant feature weights to zero, thereby reducing redundancy and improving interpretability. Three feature selection approaches were compared in preliminary experiments: stepwise selection (wrapper method), chi-squared test (filter method), and L1 regularization (embedded method). On the basis of accuracy, L1 regularization achieved the highest predictive performance and was adopted as the final method.



(a) (b)

Fig. 4. (Color online) Example of semantic segmentation applied to a fixed-point camera image. (a) Original image. (b) Segmentation result classified into snow, non-snow, obstacle, and irrelevant regions. Snow regions are shown in blue, non-snow regions in orange, obstacle regions in green, and irrelevant regions in black. This process enables the quantitative extraction of snow-covered areas on the road surface, and in this example, *SCR* is 5%.

4.4 Machine-learning-based probabilistic dispatch prediction

In this section, we present the machine learning model used to estimate the necessity of nighttime dispatch. We formulated dispatch necessity as a binary classification problem and applied a logistic regression model. The model outputs the probability that dispatch is required, taking a value between 0 and 1. This probability can be used alongside traditional experiential decision criteria, enabling more objective and reproducible nighttime decision-making.

The model is designed for ease of integration into current operational workflows. Operators can refer to the predicted probability in combination with observed conditions such as snowfall progression and road surface changes. This minimizes operational burden while enhancing decision support capabilities.

5. Evaluation and Results

In this section, we evaluate the effectiveness of the proposed snow removal dispatch support method. We first assess the reliability of the *SCR* estimated through image analysis, followed by an evaluation of the predictive performance of the machine learning model incorporating feature selection. A winter-season dataset was constructed by integrating fixed-camera images, meteorological observations, short-term forecasts, and snow depth measurements. Model performance was assessed using accuracy, precision, recall, and F1-score. Finally, we discuss the practical applicability and remaining challenges based on the obtained results.

In this evaluation, the performance of the proposed snow removal dispatch prediction method was assessed under conditions where historical meteorological data within the same winter season were available. Fixed-camera images, meteorological observations, short-term forecasts, and snow depth measurements collected during each winter season were used to construct the feature set, reflecting a realistic operational scenario in which past data accumulated within the ongoing season can be utilized. The prediction results were compared with actual dispatch decisions made by human operators under the same conditions.

In addition, to examine generalization across different seasons, models trained on multi-year datasets were evaluated on data from subsequent years. Note that this evaluation does not assume strict future-only forecasting without access to intra-season historical data nor fully automated dispatch decisions. Rather, the evaluation focuses on assessing the potential of the proposed method to support human decision-making by providing consistent and objective information when sufficient historical data within a season are available.

5.1 Overview of the dataset

To verify the effectiveness of the proposed method, we constructed a dataset by integrating fixed-point camera images, meteorological observations, short-term forecasts, and snow depth data collected during the winter season (December–March). The fixed cameras captured road surface images every 10 min at multiple locations. Each timestamp was paired with meteorological observations—such as temperature, wind speed, precipitation, relative humidity, and atmospheric pressure—as well as short-term forecasts updated hourly and available up to 11 h ahead.

Snow depth measurements recorded by the municipality were aligned with the corresponding timestamps. The presence or absence of dispatch was labeled using municipal operation logs, thereby constructing training data directly reflecting actual operational decisions. Dispatch labels were defined on the basis of snow removal operation logs provided by the snow removal contractor indicating nighttime mobilization events. Specifically, a dispatch decision was identified by the recorded dispatch start time in the log and assigned to the corresponding road route/location and decision time window. Thus, each sample represents a binary dispatch/nondispatch decision per route and time interval consistent with operational practice.

A total of 255 features were generated, as summarized in Table 1. These include time-differenced meteorological variables, moving averages, one-hot representations of wind direction and weather codes, and the *SCR* estimated by semantic segmentation.

Table 1
Feature categories and elements used for dispatch prediction. Table 1 shows the 255 features constructed from meteorological observations, short-term forecasts, image-derived SCRs, snow depth measurements, and operational history. Each feature group is organized by data source, type, and time window, and includes the total number of elements after temporal expansion. These features were used as inputs to the feature selection process and the dispatch prediction model.

Feature category	Feature type	Feature name	Time window	Total elements
Meteorological information	Observed	Weather code, temperature, wind speed, wind direction, precipitation, relative humidity, atmospheric pressure	6:00–16:00 (11 h)	77 (7 features × 1 location × 11 time steps)
Meteorological information	Forecast at 16:00	Weather code, temperature, wind speed, wind direction, precipitation, relative humidity, atmospheric pressure, relative temperature, relative index	17:00–27:00 (11 h)	99 (9 features × 1 location × 11 time steps)
Meteorological information	Difference	Temperature, wind speed, relative humidity	Current (16:00) vs Forecast (3:00 next day)	3 (3 features × 1 location × 1 time step)
Meteorological information	Mean	Temperature, temperature (absolute), wind speed, relative humidity, precipitation	6:00–16:00 (11 h)	5 (5 features × 1 location × 1 time step)
Meteorological information	Variance	Temperature, wind speed, relative humidity	6:00–16:00 (11 h)	3 (3 features × 1 location × 1 time step)
Meteorological information	Occurrence Count	Number of weather code “Snow” occurrences	6:00–16:00 (11 h)	1 (1 feature × 1 location × 1 time step)
Camera information	Observed	Ratio of snow-covered area	6:00–16:00 (11 h)	44 (1 feature × 4 locations × 11 time steps)
Snow depth sensor information	Observed	Snow depth	6:00–16:00 (11 h)	22 (1 feature × 2 locations × 11 time steps)
Snow removal operation history	Observed	Time elapsed since last snow removal operation	—	1 (1 feature × 1 location × 1 time step)

Because the dataset is imbalanced with respect to dispatch and nondispatch cases, care was taken in selecting evaluation metrics and designing train-test splits. All data were preprocessed to ensure temporal consistency, including missing-value imputation and unit normalization. These steps ensure experimental reproducibility.

The dataset comprised 67 samples in FY2022, 59 in FY2023, and 64 in FY2024. The dispatch-to-nondispatch ratios were approximately 24:43, 17:42, and 20:44 for the respective fiscal years. The number of samples differs across fiscal years because the dataset was constructed only from dates for which all required data sources (camera images, meteorological observations and forecasts, snow-depth measurements, and operation logs) were simultaneously available. Consequently, days with missing sensor data or incomplete operational records were excluded, and the effective sample size varied slightly among years.

However, because the dataset was constructed on the basis of operational records, the exact number of excluded samples cannot be strictly determined, as the start and end points of dispatch decision periods are not explicitly defined in the logs. Instead, data selection was consistently performed on the basis of the availability of all required data sources. Therefore, the number of excluded samples is considered limited and unlikely to significantly affect class balance.

5.2 Evaluation of image-based *SCR* estimation

In this section, we evaluate the reliability of the *SCR* estimated by applying semantic segmentation to fixed-point camera images captured in Rumoi City. *SCR* is an image-derived feature that quantitatively represents road surface conditions and serves as one of the main inputs to the prediction model in this study. We first evaluate the performance of the segmentation model using Intersection over Union (IoU), and then examine whether the temporal variation of *SCR* appropriately reflects actual changes in road surface conditions, thereby confirming its validity as a feature.

5.2.1 Model configuration, evaluation procedure, and estimation accuracy

The dataset used for training and evaluation was constructed by manually annotating images captured by fixed-point cameras in Rumoi City. The images were taken between 19 December 2022 and 27 January 2023, covering eight out of ten sites for which image acquisition was operationally feasible. From this period, 1–3 images were selected per day, resulting in 752 images in total. To avoid temporal bias, images were sampled at least 6 h apart. Care was taken to include diverse conditions such as snow-free surfaces, nearly fully snow-covered surfaces, and intermediate states, producing a dataset that reflects a wide range of weather conditions. Each image was manually annotated into four classes—snow, non-snow, obstacle, and irrelevant regions—and used as training data for semantic segmentation. Out of the total 752 annotated road images, 602 images were allocated to the training set and 150 images to the test set, corresponding to an approximate 80:20 split. The images were randomly assigned while maintaining diversity under snow coverage conditions.

The dataset covers multiple winter seasons and includes both typical snowfall conditions and relatively heavy snowfall events observed during the study period. Therefore, the proposed system is intended to support dispatch decisions across the practical range of snow accumulation levels encountered in routine winter road maintenance operations. Extremely rare or unprecedented heavy snowfall events beyond the observed data range were not explicitly modeled and remain outside the validated scope of this study.

The proposed system employs an encoder–decoder segmentation network based on U-Net++. The encoder (downsampling path) adopts Xception as the backbone, and multi-resolution feature maps are generated using hierarchical feature extraction blocks corresponding to the entry flow, middle flow, and exit flow of Xception. Specifically, five levels of feature maps are extracted from the input image with spatial resolutions progressively reduced to 1/2, 1/4, 1/8, 1/16, and 1/32 of the original size, and the outputs at each level are connected to the corresponding hierarchical nodes of U-Net++.

In the decoder (upsampling path), features upsampled at each resolution level are progressively fused with the corresponding encoder and intermediate node features through nested skip connections. Finally, a 1×1 convolution is applied to the highest-resolution decoder output to obtain a pixel-wise class probability map. This configuration follows the standard U-Net++ segmentation architecture with an Xception encoder widely adopted in previous studies.

Performance was evaluated using IoU, and validation images were drawn from dates not included in the training set to confirm generalization across varying weather and lighting conditions. The evaluation results showed that the mean IoU across snow, non-snow, and obstacle classes was 0.951, indicating high segmentation accuracy. Furthermore, the relationship between the predicted and ground-truth *SCR*s exhibited strong overall agreement, with very few extreme outliers. These results confirm that the *SCR* estimated via semantic segmentation appropriately reflects actual snow coverage on road surfaces.

5.2.2 Temporal validity and effectiveness of *SCR* as a feature

We assessed whether the temporal variation of *SCR* corresponds to actual changes in road surface conditions. After the onset of snowfall, *SCR* increased rapidly, indicating that the estimated *SCR* is consistent with visible changes in road conditions.

Figure 5 shows a representative temporal profile of *SCR* associated with snowfall onset. As described above, *SCR* increases rapidly after snowfall begins. Notably, the observed precipitation amount at the onset was as low as 0.4 mm/h, which is far below the threshold for “moderate rain” (10 mm/h) defined by the Japan Meteorological Agency (JMA) classification of rainfall intensity.(19) This indicates that even a minimal precipitation event can trigger a rapid increase in *SCR*. This observation supports the temporal validity of *SCR* as a feature reflecting road surface snow coverage. Comparisons with snow depth sensor values and precipitation measurements further indicated synchronized fluctuation patterns, demonstrating that *SCR* derived from image analysis provides a depiction of road surface conditions, which is consistent with meteorological data.

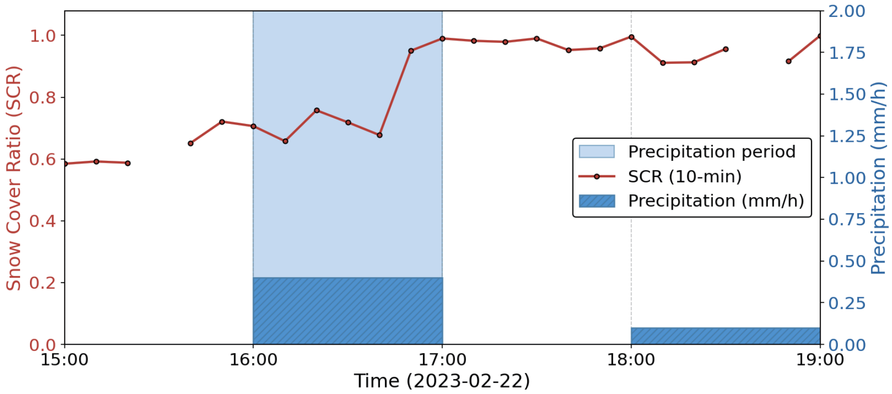


Fig. 5. (Color online) Temporal profile of *SCR* and precipitation during a snowfall event. Time series of *SCR* (10 min interval) and precipitation (hourly) from 15:00 to 19:00 on February 22, 2023. The shaded area indicates the precipitation period (16:00–16:50, 0.4 mm/h). Prior to precipitation onset, *SCR* ranged from 0.58 to 0.72; it then rose rapidly to 0.95 during the precipitation period and remained elevated at approximately 0.96 after precipitation ceased. The precipitation intensity (0.4 mm/h) is well below the Japan Meteorological Agency's threshold for "moderate rain" (10 mm/h),[19] indicating a light snowfall event.

These results indicate that *SCR* is not merely a pixel ratio but a reliable quantitative indicator that captures changes in road surface conditions. Moreover, incorporating *SCR* as a feature enables the prediction model to better detect small initial accumulations and localized changes, contributing to the improved dispatch prediction accuracy described later.

On the basis of these findings, we conclude that *SCR* estimation using semantic segmentation is valid and effective as an input feature for the dispatch DSS. The behavior of *SCR* immediately after snow-removal operations was not consistently observable in the available data owing to factors such as partial clearing, camera field of view, and illumination conditions. Therefore, a detailed analysis of post-removal *SCR* dynamics is left for future work.

5.3 Evaluation of feature selection and prediction models

In this section, we evaluate the effectiveness of feature selection methods for the snow removal dispatch prediction model and assess the predictive performance of the learning model using the selected features. First, we compare three methods—L1 regularization, stepwise selection, and the chi-square test—using fivefold cross-validation for each fiscal year to identify the method that provides the most stable and accurate predictions. In addition, we compare the model's performance with the actual dispatch decisions made by the snow removal decision operator, thereby assessing its practical usefulness. Finally, we assess extrapolation performance using a time-series split in which models are trained on past years and validated on future years to evaluate robustness under annually varying meteorological conditions.

The operator decisions were made using fixed-point camera images, meteorological observations, patrol confirmation, and experience-based heuristics. In FY2023 and FY2024, the operator also had access to the system's dispatch prediction outputs during actual operations.

Decisions were made per route and decision time window consistent with snow removal contractor dispatch practice. While the proposed model utilized integrated heterogeneous sensing data including *SCR*-derived indicators, part of this predictive information was shared with the operator in later years. Therefore, the comparison in FY2023–FY2024 represents system-supported human decision-making, implying a conservative comparison.

5.3.1 Comparison of feature selection methods

The comparison of feature selection methods using annual datasets showed that L1 regularization achieved the most stable and highest performance. As shown in Table 2, the accuracies obtained by L1 regularization were 0.890 in FY2022, 0.919 in FY2023, and 0.853 in FY2024, all of which were high with small fluctuations across years. In contrast, the decision accuracies of the operator decisions were 0.851 in FY2022, 0.809 in FY2023, and 0.641 in FY2024. In every fiscal year, the model using L1 regularization outperformed the operator decisions, with a particularly large margin observed in FY2023, where the model achieved 0.919 compared with the operator decisions' 0.809.

The relatively low operator accuracy observed in FY2024 may be attributed to increased variability in snowfall patterns and a strong degree of class imbalance compared with other years, which likely increased decision difficulty under operational conditions. While this difference should be considered when interpreting the comparison, the model maintained higher accuracy across all fiscal years, supporting the overall validity of the comparison.

The features selected through L1 regularization primarily included short-term forecast precipitation, weather codes, wind direction, snow depth, and *SCR*—factors directly associated with dispatch decisions. This ensures interpretability and practical validity. On the basis of these results, we concluded that L1 regularization is the most suitable feature selection method for this study.

5.3.2 Evaluation of year-to-year prediction performance

Next, to assess extrapolation performance under meteorological conditions that vary substantially across years, we conducted an evaluation using time-series splits in which models were trained using earlier fiscal years and tested on subsequent years. As shown in Table 3, the accuracy of the model trained on FY2022 data and tested on FY2023 was 0.725, whereas that of the model trained on FY2023 and tested on FY2024 was 0.672. These accuracies were lower than those obtained through within-year cross-validation because meteorological factors such as

Table 2
Classification accuracy obtained by three feature selection methods and the operator decisions for each fiscal year. Fivefold cross-validation accuracy for L1 regularization, stepwise selection, and the chi-square test using FY2022, FY2023, and FY2024 data. For reference, the accuracy of the operator decisions is also included. Values represent the mean accuracy for each fiscal year.

Fiscal year	L1 regularization (embedded method)	Stepwise selection (wrapper method)	Chi-square test (filter method)	Operator decisions
2022	0.890	0.802	0.785	0.851
2023	0.919	0.858	0.790	0.763
2024	0.853	0.869	0.741	0.641

Table 3
Year-to-year prediction accuracy and the effect of multi-year training. Prediction accuracy obtained when training and testing are conducted on different fiscal years (time-series split). The table also includes the accuracy obtained when training on combined FY2022–FY2023 data and testing on FY2024. Precision, recall, and F1-score corresponding to each setting are listed together with accuracy.

Training data	Test data	Accuracy	Precision	Recall	F1-score
FY2022	FY2023	0.725	0.365	0.536	0.433
FY2022	FY2024	0.694	0.220	0.522	0.309
FY2023	FY2024	0.672	0.400	0.471	0.432
FY2022–FY2023	FY2024	0.747	0.350	0.687	0.463

snowfall amount, temperature, and precipitation timing differ across years, resulting in distribution shifts between training and test data.

When compared with operator decision performance, the model trained on FY2023 data outperformed the operator decisions in FY2024 (0.672 vs 0.641), demonstrating that even single-year models can surpass human judgment in cross-year prediction. Furthermore, the model trained on combined FY2022–FY2023 data achieved an accuracy of 0.747 for FY2024, consistently exceeding the operator decision accuracy of 0.641. This confirms that learning from multiple years of diverse meteorological patterns substantially improves extrapolation performance. Although statistical significance tests were not conducted, the consistent superiority across multiple years suggests robustness.

Precision, recall, and F1-score also showed similar trends: models trained on multiple years maintained a higher performance than single-year models and often surpassed the accuracy of the operator decisions. Owing to space limitations, detailed values are presented in Table 3.

5.4 Discussion

In this section, we discuss the proposed snow removal dispatch DSS from both technical/system and practical usability perspectives. In Sect. 5.4.1, we examine the technical contributions and positioning relative to prior DSS approaches, while in Sect. 5.4.2, we evaluate practical usability on the basis of field feedback and operational considerations.

5.4.1 Technical and system value

On the basis of the evaluation results presented above, we discuss the technical and system-level value of the proposed snow removal dispatch decision support system (DSS). The *SCR* estimated through image analysis achieved high segmentation accuracy (IoU = 0.951) and successfully captured temporal changes associated with snowfall onset, melting, and post-removal clearing. Because *SCR* provides a quantitative and spatially localized representation of road surface snow conditions, it stabilizes early-stage situational assessment that has traditionally relied on subjective visual interpretation. Thus, *SCR* serves as a reliable sensing-derived indicator for dispatch decision-making.

The dispatch prediction model integrating meteorological observations, short-term forecasts, snow depth, and *SCR* demonstrated stable and high performance across multiple fiscal years, consistently exceeding operator planning accuracy. Feature selection using L1 regularization concentrated on physically interpretable snowfall-related variables, achieving a balance between predictive accuracy and model interpretability required for operational deployment.

Furthermore, integrating *SCR*-based visualization and prediction outputs within the information-sharing interface enables consistent and objective situation awareness prior to dispatch planning. Because the model provides probabilistic predictions, it improves reproducibility and reduces variability in human decision-making under nighttime operational constraints.

To further clarify the positioning of the proposed approach relative to prior DSSs for winter road management, Table 4 shows key differences between representative prior approaches reviewed in Sect. 2 and the proposed system in terms of input data, prediction targets, operational assumptions, evaluation design, and operational interface.

As shown in Table 4, prior DSS studies typically rely on meteorological observations or rule-based thresholds and focus on snowfall or road condition indicators, whereas the proposed system integrates heterogeneous sensing data including image-derived *SCR* and directly predicts dispatch necessity. Moreover, the proposed approach combines feature-selection-based prediction with an operational user interface supporting real-world decision-making, thereby providing an integrated decision-support framework extending beyond conventional DSS implementations. This integration of heterogeneous sensing and prediction information constitutes the primary technical contribution of the proposed DSS. Unlike prior DSS approaches that typically report rule accuracy or simulation performance, the proposed method evaluates dispatch prediction accuracy on the basis of real operational data.

5.4.2 Practical usability

To further examine practical usability as an operational DSS, supplementary qualitative evaluation was conducted through interviews with one dispatch operator and questionnaire responses from five field workers involved in snow removal operations. Participants were asked to evaluate the usefulness of *SCR* visualization and prediction outputs for road condition recognition, dispatch decision confidence, and patrol workload reduction, using structured questionnaire items and semistructured interview questions. Participants reported that *SCR* visualization improved the recognition of localized snow accumulation and early road condition changes, while prediction outputs supported consistent dispatch decisions under uncertain

Table 4
Comparison of representative prior winter road maintenance DSSs reviewed in Sect. 2 with the proposed snow removal dispatch support system, highlighting differences in input data type, prediction target, operational assumption, evaluation design, and operational user interface.

Aspect	Representative prior DSS	Proposed system
Input data	Meteorological observations, road sensors	Meteorology + camera + snow depth + *SCR*
Prediction target	Snowfall or road condition thresholds	Dispatch necessity
Operational assumption	Rule-based or threshold decision	Data-driven prediction with operator support
Evaluation design	Simulation or rule accuracy	Historical dispatch prediction accuracy
Operational interface	Limited or not integrated	Integrated decision-support UI

meteorological conditions. The operator noted that the integrated display enabled remote road condition assessment and reduced the need for nighttime patrol confirmation in some situations.

These findings indicate that the practical utility of the proposed DSS arises from the integrated presentation of *SCR*-based visualization and prediction outputs supporting operator situation awareness and decision consistency. The system was perceived as operationally useful and acceptable within existing winter road maintenance workflows, suggesting potential benefits such as reduced patrol workload and standardized dispatch criteria. Thus, beyond component-level accuracy improvements, the proposed system demonstrates practical value as a human-in-the-loop snow removal dispatch DSS.

6. Conclusions

In this study, we proposed a decision support method for snow removal dispatch integrating fixed-camera images and meteorological information, with the aim of assisting human operators in nighttime winter operations. The effectiveness of the proposed method was evaluated through a reliability assessment of the image-derived *SCR* and an examination of snow removal dispatch prediction performance using a machine learning model with feature selection.

The evaluation of *SCR* estimation confirmed high segmentation accuracy and demonstrated that the temporal variations in *SCR* appropriately reflect changes in road surface conditions. These results indicate that *SCR* derived from fixed-camera images serves as an effective road condition indicator that can support snow removal dispatch decisions.

In the evaluation of the dispatch prediction model, the model incorporating L1-regularization-based feature selection outperformed human decision accuracy across all evaluated years. Furthermore, training with multi-year data improved prediction performance across different years, indicating a certain level of generalization capability of the proposed method.

Overall, these results suggest that the proposed method effectively complements human decision-making in nighttime operations and contributes to improving the consistency and objectivity of snow removal dispatch decisions.

From a sensing perspective, the proposed method demonstrates the practical value of integrating heterogeneous environmental sensing modalities—fixed-camera imaging, snow-depth measurement, and meteorological sensing—for representing road surface conditions relevant to operational decision-making. The results highlight how sensor-derived indicators such as *SCR* can bridge environmental sensing and human-in-the-loop decision support in winter road maintenance.

Future work includes (1) evaluating generalization performance using data from different regions and additional years, (2) conducting a detailed analysis of *SCR* estimation accuracy under varying meteorological and illumination conditions, (3) improving the interpretability of factors contributing to dispatch decisions, and (4) verifying practical effectiveness through large-scale field evaluations. Through these efforts, the general applicability and practical effectiveness of the proposed method will be further enhanced, contributing to snow removal operation support in a wide range of regions.

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