Analysis of Weather Information and Road Surface Images for Snow Removal Dispatch Prediction

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***Abstract*—This study focuses on addressing the challenges associated with decision-making in winter road snow removal operations, aiming to alleviate the burden on snow removal personnel. Specifically, we propose a system that collects and visualizes information on road weather data and snow conditions to support decision-making by responsible personnel. Additionally, by sharing the collected information, we aim to facilitate the sharing of premonitions about changes in decision-making among snow removal personnel, reducing the need for physical inspections. In this paper, we discuss the utilization of the collected information, presenting a module proposal that utilizes deep learning to quantify the snow coverage in images captured by fixed-point cameras. We also explore the analysis of data for the introduction of a predictive function for snow removal operations.**

***Keywords*—Snow Removal, Information Sharing System, Weather Information.**

I. INTRODUCTION

Winter road snow removal operations play a critical role in maintaining road traffic and essential infrastructure in snowy regions. One significant challenge in these operations is the difficulty of decision-making regarding deployment.

The decision to deploy snow removal operations is made by responsible personnel, determining whether to conduct snow removal activities from 16:00 to 2:00 the next day. Snow removal tasks encompass two main types: ”new snow removal” and ”road surface leveling.” New snow removal aims to eliminate accumulated snow on road surfaces when it poses a hindrance to road traffic due to heavy snowfall. Road surface leveling is performed to ensure road flatness when conditions like compacted snow growth or residual snow impede traffic.

Particularly, the decision-making for new snow removal operations scheduled from 2:00 the next day is heavily influenced by road conditions up to that point and localized weather changes after 16:00. Even veteran personnel often overturn their decisions made at 16:00, leading to frequent decision reversals.

Due to the frequent reversals in deployment decisions, snow removal personnel are burdened with the need to be prepared for deployment even if it was deemed unnecessary at 16:00. Additionally, a pre-deployment assessment called ”snow patrols” involves physically traveling to the snow removal area by car just before the operation to visually confirm the snow conditions. However, driving on snow-covered roads late at night poses risks of vehicle stacking and slip accidents, necessitating alternative methods.

To alleviate the burdens associated with such snow removal deployment decisions, this study adopts an approach based on Visual Analytics, utilizing a visual interface for analytical reasoning concerning large and complex datasets [1]. We aim to develop a system that collects and visualizes information on road snow conditions and weather data to support decision-making by personnel. As part of the functionality of the proposed snow removal deployment decision support system, we implement a feature to capture real-time road images from fixed cameras in the target area and gather meteorological information.

The collected information is visualized on the system to aid decision-making by personnel, enabling consistent deployment decisions that are not affected by weather fluctuations, ultimately reducing the effort required for snow patrols. Furthermore, by making the information accessible to snow removal personnel, we aim to facilitate the sharing of premonitions about changes in deployment decisions due to weather fluctuations.

In this paper, we describe the structure of a snow-related information sharing site that has been launched as part of the snow removal deployment decision support system. We also propose a snow coverage estimation module using deep learning to automate the visual inspection of snow coverage

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in fixed camera images for the site.

Moreover, we consider introducing a snow removal deployment prediction feature to assist in making advanced deployment decisions. The decision to carry out snow removal operations at 16:00 the day before requires considering the snow conditions and weather changes, making it a challenging task even for experienced personnel. To address this, we develop an algorithm to predict the necessity of snow removal based on the collected information and validate its effectiveness by introducing the system into real-world scenarios.

II. Related Research

In this section, we discuss research on prediction systems related to snow removal deployment support systems and explore relevant technologies in image processing used for snow coverage estimation.

A. Research on Systems Using Prediction Techniques

In tandem with the development of snow removal deployment prediction functionality, there exists research focusing on forecasting related demands to facilitate appropriate responses.

One of Japan's challenges revolves around anticipating the increase in the elderly population and the decrease in the working-age population. In light of this, it is crucial to consider the efficient optimization of emergency ambulance transport services for the long term. Addressing this, Okamoto et al.'s research [2] proposes an emergency ambulance transport demand prediction model to enhance the efficient operation of emergency medical transport services. The study validates the suitability of the emergency transport demand prediction model using data from Matsuyama City. Additionally, the research reports insights, such as significantly higher transport rates per capita for the age group of 75 and above, variations in demand based on season, day of the week, and time.

Focusing on the pressing issue of heatstroke, Inai et al.'s study [3] analyzes emergency dispatch data related to heatstroke at a granular level. The objective is to formulate sustainable measures for future heatstroke incidents. The study specifically tackles the prediction of the number of heatstroke patients for adaptation in emergency medical scenarios, demonstrating the feasibility of predicting heatstroke patient numbers from meteorological data.

Addressing the challenge of pedestrians' falls on snow-covered walkways in Sapporo, Kato et al.'s research [4] deals with predicting the occurrence of emergency transport due to falls on such walkways. Using deep learning and past daily emergency transport data, the study constructs a model to predict the number of emergency transports resulting from falls on extremely slippery surfaces formed on sidewalks and pedestrian crossings.

Moreover, research has been conducted to maintain safe and efficient traffic in snowy regions during winter. Takahashi et al.'s study [5] aims to predict the winter road conditions to ensure proper management of road infrastructure. The research, initiated in 2004, observes weather and road surface temperature and develops a prediction model, operating a prototype in 2005.

Hori et al.'s study [6] focuses on constructing a winter road surface freezing prediction system to support the pre-spraying of anti-freezing agents. Using neural networks and discriminant analysis, the study builds a model to detect the temporal variations in road surface temperature and moisture. The established prediction system proves capable of accurately forecasting road surface freezing three hours ahead.

In connection with these studies, our research aims to develop a prediction system for the necessity of snow removal deployment to support the intricate decision-making process and validate its effectiveness by introducing the system into real-world scenarios.

B. Semantic Segmentation

Semantic segmentation refers to the image recognition task using deep learning that divides an image into pixels and assigns semantic labels to each pixel. Since the introduction of Fully Convolutional Network (FCN) by Long et al. [7], methods based on the structure of FCN have become fundamental in this field. To obtain high-resolution feature maps, an Encoder-Decoder structure is commonly employed, utilizing FCN as the Encoder and incorporating the feature maps into the Decoder to recover spatial information. Representative models within this framework include Seg-Net [8] and U-Net [9]. Seg-Net performs downsampling in the Encoder and then upsampling in the Decoder corresponding to the number of downsampling steps. It utilizes the spatial indices of the maximum values in each pooling layer during upsampling, enabling clearer inferences. U-Net, while sharing the Encoder-Decoder structure with Seg-Net, adopts skip connections that concatenate low-dimensional features with high-dimensional ones, serving as a means to recover information lost during downsampling. Additionally, other methods, such as PSP-Net [10] and DeepLab [11] have been proposed, contributing to diverse research in this domain.

Furthermore, there is research that performs segmentation using images overlooking road surfaces targeted for heating to determine the snow coverage. In Imahara's study [12], snow detection in images captured from an approximately 30-meter height overlooking parking lots in Sapporo city was conducted. The results demonstrated reliable accuracy in snow detection, indicating its suitability for controlling road heating systems.

This study employs semantic segmentation for snow coverage estimation. Currently, snow removal decisions rely on manual inspection of images captured by fixed-point cameras installed at snow removal sites. To automate the assessment of snow conditions observed in these images, the study turns to semantic segmentation. Treating snow coverage estimation from images as a regression problem presents challenges, particularly in handling obstacles, such as cars, buildings, and people that may interfere with image recognition. Preprocessing is essential, and it involves addressing the significant amount of work required due to potential movements of obstacles and changes in camera angles. Attempting to estimate

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obstacle regions through semantic segmentation alleviates this workload. Moreover, considering each pixel as a piece of training data allows handling a larger dataset compared to treating snow coverage estimation as a regression problem. This approach also enables leveraging information about regions prone to heavy or light snow coverage.

III. Data for Snow Removal Decision Support System

In this section, we will discuss the data to be visualized in the system developed for supporting decision-making in snow removal operations.

A. Visualization Target Data

The system developed in this study collects and visualizes data from five snow removal points in Rumoi City, Hokkaido. Two fixed-point cameras are installed at each location, capturing road images from different angles to provide a detailed understanding of the snow accumulation situation. The data visualized in the system includes the following four components:

Images from Fixed-Point Cameras: Real-time road images captured by network cameras installed at each location.

Snow Coverage Percentage from Image Analysis: The percentage of snow coverage in the area of the road captured by the camera images, obtained through semantic segmentation analysis.

Weather Information: Weather forecast information provided by WeatherNews [13]. The short-term forecast includes hourly weather forecasts up to 72 hours in advance, and the medium-term forecast provides daily weather forecasts up to 10 days in advance. The short-term forecast includes weather codes, temperature, precipitation, atmospheric pressure, wind speed, wind direction, and relative humidity. The medium-term forecast includes weather codes, maximum temperature, minimum temperature, and precipitation probability.

Snow Depth Information: Snow depth information provided by WeatherNews [13]. Snow depth is presented in centimeters, assuming snow accumulation on the ground. It includes a 10-minute observation of snow depth and a 60-hour forecast with hourly intervals.

Snow Removal Operation Prediction Probability: The probability of the prediction for the need for snow removal operation based on the collected visualization data. This probability is generated by a logistic regression model using input features, such as estimated snow coverage percentage, weather information, and snow depth information. The algorithm for snow removal operation prediction is illustrated in Fig. 1.

Weather information and snow depth information can be obtained in detail for each snow removal point by specifying the latitude and longitude.

IV. Development of Snow Removal Dispatch Decision Support System

The proposed system aims to achieve the following objectives: i) Enable personnel responsible for deployment decisions to make decisions that are not overturned afterward, ii) Reduce the effort of snow patrols, iii) Allow snow removal personnel to access the same information as the deployment decision-makers to prepare for deployment.

A. System Configuration

The configuration of the snow removal dispatch decision support system is illustrated in Fig. 2. The system comprises four main components: client-side, server-side, database, and external data.

External data includes images captured by fixed-point cameras, weather information, and snow depth information. The server-side retrieves and stores this external data in the database. Through API integration, the server-side enables the client-side to access the stored data consistently.

The technology stack used for developing this system includes:

- Client-side: JavaScript, React
- Server-side: Python, FastAPI
- Database: MySQL

B. System Functions

The proposed system encompasses the following features:

1. **Real-time Display of Fixed-Point Camera Images at Snow Removal Target Locations:** A function to display real-time images from fixed-point cameras at snow removal target locations.

2. **Display of Weather Information and Snow Depth for Decision-Making in Snow Removal Operations:** A function to display weather information and snow depth data used in the decision-making process for snow removal operations.

3. **Utilization of Collected Data:**

Snow Coverage Estimation Function: Applies deep learning to fixed-point camera images to estimate the percentage of the snow-covered area in the road surface. - Learning Model: Utilizes Unet++, a model highly rated for semantic segmentation tasks, with Xception [14] network architecture for feature extraction in the encoder. - Pre-training: Utilizes a pre-trained model on the Imagenet dataset.

Snow Removal Operation Prediction Function: Applies a prediction model to collected data to forecast the necessity of snow removal operations. - Prediction Model: Utilizes logistic regression, effective for binary classification problems, providing ease of interpretation due to its simplicity.

Users can input and view information through the following screens on the client side.

Location Selection Screen: A screen displaying all snow removal target locations, allowing the selection of a specific location for information viewing. For each displayed

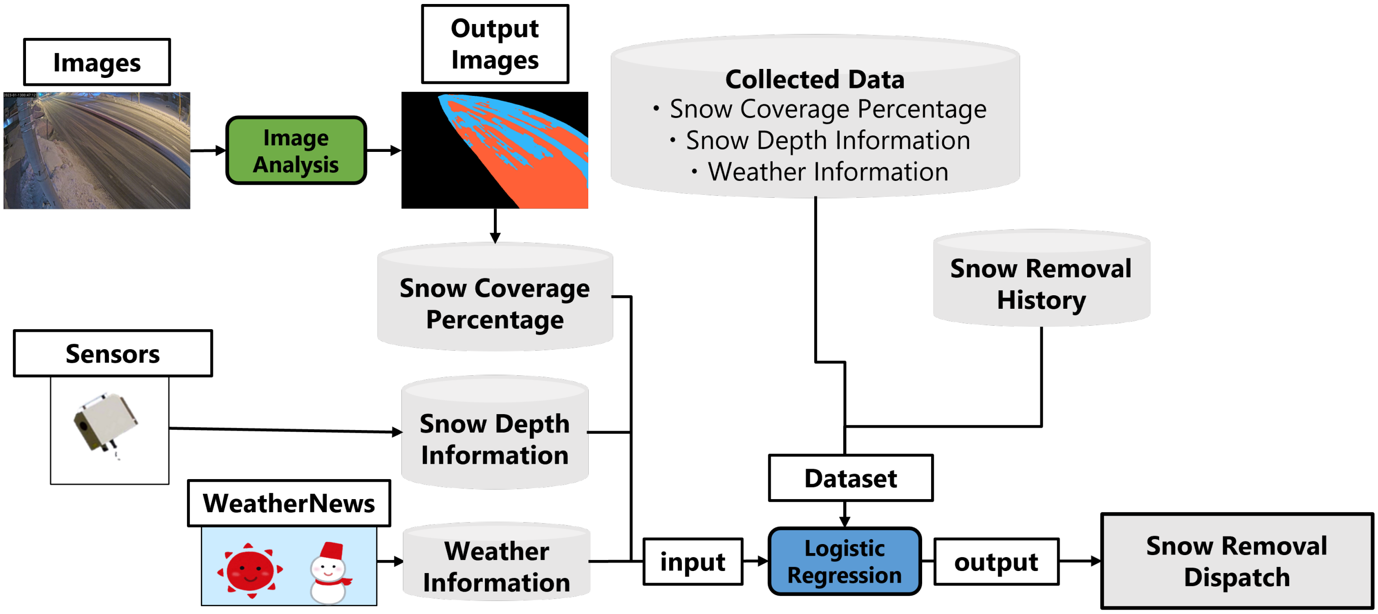

Fig. 1. Snow Removal Operation Prediction Algorithm.

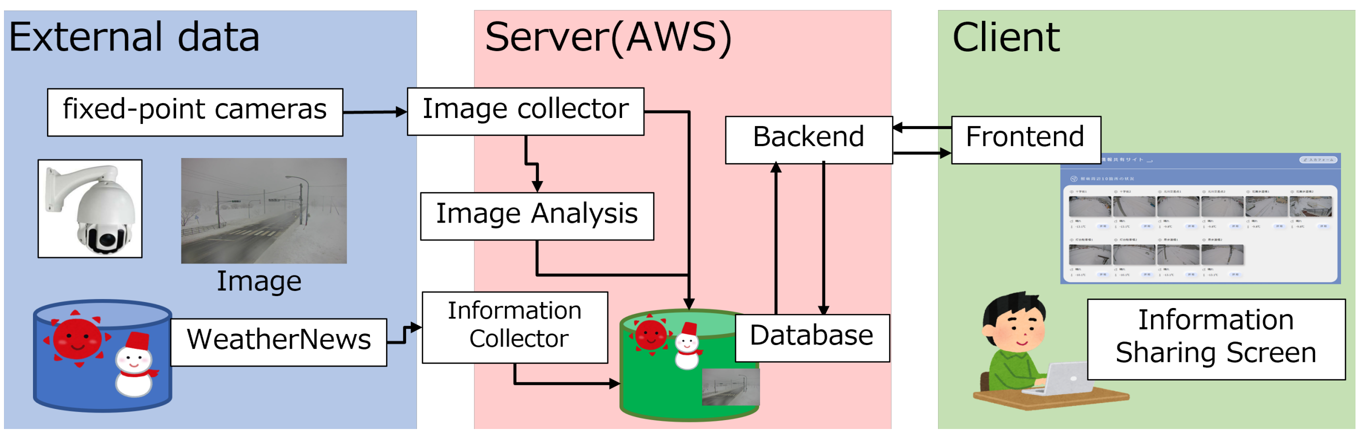

Fig. 2. Overview of System Configuration.

location, real-time images from fixed-point cameras and their update timestamps are shown. A specific layout is illustrated in Fig. 3.

Real-time Information Screen for Each Location: A screen presenting real-time images from fixed-point cameras, along with weather information and snow depth data for the selected location.

Historical Information Screen for Each Location: A screen displaying historical images from fixed-point cameras and past weather information, along with snow depth data for the chosen location. Graphical visualization of weather information and snow depth data facilitates the understanding of temporal trends.

Forecast Information Screen for Each Location: A screen presenting weather forecast information and snow depth forecast information for the selected location. Visualizing forecast data aids in understanding temporal patterns.

Snow Depth Input Form Screen: A screen for snow removal personnel to input measured snow depth values.

V. System Effectiveness Verification

The percentage of snow-covered areas in road images significantly influences the decision-making process for snow removal operations. Therefore, automatic analysis through semantic segmentation plays a crucial role in the utility of the proposed system. Analyzing the results of this analysis along with collected data and the historical records of operational decisions made by responsible personnel, we develop an operational prediction feature.

In Section II-B, we discussed the technology to automate and quantify the visual confirmation of snow conditions from fixed-point camera images using semantic segmentation. In this section, we apply this technology to verify the accuracy of snow coverage estimation.

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Fig. 3. Site Selection Screen.

Furthermore, by analyzing the estimated snow coverage, weather information, snow depth data, historical operational decisions made by responsible personnel, and operational records, we develop an automated and quantified operational prediction feature.

A. Accuracy Verification of Snow Coverage Estimation Using Deep Learning

For the accuracy verification of snow coverage estimation using deep learning, we evaluate the accuracy of region estimation and snow coverage percentage estimation as evaluation metrics.

1) Dataset: We use the fixed-point camera images mentioned in Section III-A. For this verification, we use images from 8 out of 10 locations due to labeling and system constraints. The shooting period is from December 19, 2022, to January 27, 2023. From this period, we select around 1 to 3 images from the same day, resulting in a dataset of 752 images. The image selection aims to cover different time intervals and weather conditions, including situations with no snow, heavy snow, and various other conditions.

Regarding labeling, we define the following labels for each pixel in the image: - Snow: Label for the region of the road surface with confirmed snow. - Non-snow: Label for the region of the road surface with no confirmed snow. - Obstacle: Label for objects that may interfere with the classification of snow and non-snow regions, such as buildings, vehicles, trees, people, and poles. - Irrelevant Region: Label for all regions not classified into the above three classes.

TABLE I
TRAINING PARAMETERS.

Epochs	40
Mini-Batch Size	2
Optimization	Adam
Learning Rate	Initial: 0.0001 After 25 epochs: 0.00001

2) Training Configuration: The training parameters are shown in Table I.

We distribute the dataset into training and validation images at an 8:2 ratio for each location and date. This separation allows us to evaluate the accuracy of predictions on images taken on different dates than those used for training, providing a more accurate estimation of system performance during actual operations.

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3) Evaluation Metrics: The Intersection over Union (IoU) is used as the evaluation metric for label accuracy.

4) Snow Coverage Estimation Method: We utilize the snow coverage estimation proposed by ImaHara et al. [12] using the snow coverage percentage. The snow coverage percentage for each image is defined by 1.

We evaluate whether this value can be used to automate and quantify visual confirmation of snow conditions.

5) Verification Results: The IoU result is 0.951, indicating successful training.

For the 172 validation images, we calculate the snow coverage percentage using 1. The confusion matrix for the snow coverage percentage is shown in Table II.

In most images, the snow coverage percentages from the ground truth and predictions are in close agreement, with no significant outliers.

B. Data Analysis for the Development of Snow Removal Dispatch Prediction Function

In this section, we apply the results of the snow coverage estimation, as verified in Section V-A, to the collected fixed-point camera images. We also analyze weather information, snow depth information, snow removal dispatch history, and the dispatch decisions made by responsible personnel. This analysis aims to explore an algorithm for predicting snow removal dispatch.

1) Utilized Data: We describe the data used for the analysis. The data covers the period from December 24, 2022, to February 28, 2023, for all 10 locations with fixed-point cameras mentioned in Section III-A.

For 8 out of the 10 locations, we use data for 63 days, excluding 4 days with data defects on February 15, 18, 27, and 28. For the remaining 2 locations with data defects, we use data for 36 days, excluding the same 4 days. Additionally, we use data from two laser snow depth sensors installed in different locations.

We utilize the snow coverage percentage estimates from the fixed-point camera images, as discussed in Section V-A. These estimates are obtained by applying the verification results to images taken at 4-hour intervals each day.

Weather information includes precipitation, temperature, and wind speed, provided by WeatherNews for each fixed-point camera location. Forecast information is available at 20, 24, and 28 hours.

Snow depth information is measured by laser snow depth sensors installed along the road. Two sensors are located approximately 10 km away from the fixed-point camera installation points.

Finally, we use the snow removal dispatch history in Rumoi City during the same period, as well as the recorded dispatch decisions made by responsible personnel at 16:00 on the previous day. These records are binary variables, indicating whether there was a dispatch (1) or not (0).

2) Analysis Method: We investigate the correlation between the snow removal dispatch records and various data collected at 16:00 on the previous day. We focus on identifying highly correlated variables to use in the prediction model.

3) Analysis Results: The correlation coefficients between the snow removal dispatch records and various data at 16:00 on the previous day, the change in estimated snow coverage percentage, and forecast data are presented in Tables III, IV, and V, respectively.

The tables indicate that the estimated snow coverage percentage, snow depth, temperature, and forecast data at 20:00, wind speed at 24:00, and precipitation at 28:00 exhibit strong correlations, with correlation coefficients exceeding

C. Evaluation of Generalization Performance for Snow Removal Dispatch Prediction

Based on the data analysis presented in Section V-B, we explore an algorithm for predicting snow removal dispatch and investigate its generalization performance. The evaluation involves conducting a 5-fold cross-validation and comparing the results with the accuracy of dispatch decisions made by responsible personnel.

1) Experimental Setup: We describe the experimental settings, including the data used and the prediction algorithm.

Firstly, we use the data mentioned in Section V-B1, focusing on variables with an absolute correlation coefficient of 0.3 or higher, as identified in the analysis results.

Next, we consider the prediction algorithm. We apply logistic regression to generate output values for each location, and the prediction result is the average of these values for the same day.

2) Validation Method: We describe the validation method. We conduct a 5-fold cross-validation, ensuring that the ratios of observation locations and target variables are equal during data splitting. By specifying a seed value during the splitting, multiple datasets are created. Comparing the prediction results for these datasets allows us to investigate generalization performance independent of the dataset. Evaluation metrics, such as accuracy, precision, recall, and F1 score are examined, and the results are compared with dispatch decisions made by responsible personnel.

3) Validation Results: We present the validation results. Table VI shows the generalization performance obtained through 5-fold cross-validation for datasets created with seed values ranging from 0 to 4.

TABLE VI
GENERALIZATION PERFORMANCE EVALUATION THROUGH 5-FOLD CROSS-VALIDATION.

Seed Value	Accuracy	Precision	Recall	F1 Score
0	0.746	0.571	0.632	0.600
1	0.778	0.667	0.526	0.588
2	0.794	0.650	0.684	0.667
3	0.683	0.467	0.368	0.412
4	0.762	0.600	0.632	0.615

Additionally, Table VII displays the results when unstable model coefficients are excluded, focusing on stable model parameters.

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$$\text{Snow Coverage Percentage} = \frac{\text{Number of Pixels with Snow Label}}{\text{Number of Pixels with (Snow Label + Non-snow Label)}} \tag{1}$$

TABLE II
CONFUSION MATRIX FOR SNOW COVERAGE PERCENTAGE.

		Actual Snow Coverage Percentage										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Predicted Snow Coverage Percentage	0.0	2	0	0	0	0	0	0	0	0	0	0
	0.1	9	22	0	0	0	0	0	0	0	0	0
	0.2	0	4	2	0	0	0	0	0	0	0	0
	0.3	0	1	1	0	0	0	0	0	0	0	0
	0.4	0	1	0	0	0	0	0	0	0	0	0
	0.5	0	0	0	0	1	0	0	0	0	0	0
	0.6	0	0	0	0	0	0	0	0	1	1	0
	0.7	0	0	0	0	0	0	0	0	0	0	0
	0.8	0	0	0	0	0	0	0	0	0	0	0
	0.9	0	0	0	0	0	0	0	0	0	0	1
	1.0	0	0	0	0	0	0	0	0	0	0	126

TABLE III
CORRELATION COEFFICIENTS BETWEEN SNOW REMOVAL DISPATCH RECORDS AND DATA AT 16:00 ON THE PREVIOUS DAY.

Data Name	Correlation Coefficient
Estimated Snow Coverage Percentage	0.334
Snow Depth (Furuyama)	0.378
Snow Depth (Touge-shita)	0.403
Temperature	-0.490
Precipitation	0.182
Wind Speed	0.318

TABLE IV
CORRELATION COEFFICIENTS BETWEEN SNOW REMOVAL DISPATCH RECORDS AND CHANGE IN ESTIMATED SNOW COVERAGE PERCENTAGE.

Data Name	Correlation Coefficient
Difference from 12 hours ago	-0.218
Difference from 8 hours ago	-0.199
Difference from 4 hours ago	-0.082

TABLE V
CORRELATION COEFFICIENTS BETWEEN SNOW REMOVAL DISPATCH RECORDS AND FORECAST DATA.

Forecast Time	Data Name	Correlation Coefficient
20:00	Temperature	-0.326
	Precipitation	0.355
	Wind Speed	0.434
24:00	Temperature	-0.246
	Precipitation	0.284
	Wind Speed	0.323
28:00	Temperature	-0.230
	Precipitation	0.349
	Wind Speed	0.249

TABLE VII
GENERALIZATION PERFORMANCE EVALUATION THROUGH 5-FOLD CROSS-VALIDATION WITH STABLE MODEL COEFFICIENTS.

Seed Value	Accuracy	Precision	Recall	F1 Score
0	0.857	0.750	0.789	0.769
1	0.857	0.813	0.684	0.743
2	0.841	0.714	0.789	0.750
3	0.794	0.688	0.579	0.629
4	0.810	0.684	0.684	0.684

Furthermore, Table VIII presents the results of dispatch decisions made by responsible personnel during the same period.

TABLE VIII
DISPATCH DECISIONS MADE BY RESPONSIBLE PERSONNEL.

Accuracy	Precision	Recall	F1 Score
0.714	0.520	0.684	0.591

The results show that the proposed dispatch prediction algorithm demonstrates superior accuracy compared to the dispatch decisions made by responsible personnel. Additionally, examining the model coefficients and refining parameters lead to higher prediction accuracy. We plan to implement this prediction algorithm and display it on the snow-related information sharing site in the future.

VI. CONCLUSION AND FUTURE WORK

In this paper, we provided an overview of a snow-related information sharing site, which is part of the snow removal dispatch decision support system and is already in practical use. The snow-related information sharing site automatically collects real-time road images and meteorological information for snow removal points, visualizes them on the site, and allows not only dispatch decision-makers but also snow removal personnel to access and share relevant information. We also outlined the verification of the introduction effects of the snow removal dispatch decision support system in the future.

Furthermore, we discussed our efforts in using deep learning for snow coverage estimation based on captured images from fixed-point cameras, presenting the results and potential applications of the method. Additionally, we proposed an algorithm to predict snow removal dispatch based on data collected at 16:00 on the day before the dispatch, highlighting its potential as a snow removal dispatch prediction feature.

Looking ahead, our future plans involve continued development of the snow removal dispatch prediction feature and its

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implementation into the system. Subsequently, we will evaluate the accuracy of the dispatch prediction, its contribution to reducing the burden on decision-makers, alleviating the workload of snow patrols, and reducing the psychological burden on snow removal personnel through information access. These assessments will guide our ongoing efforts and contribute to the refinement of the snow removal dispatch decision support system.

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