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Investigation on the Use of Polarized Images for Frozen Road Surface Recognition

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Abstract— **In this study, we investigate the optimal capture conditions and features for recognizing frozen road surface conditions using polarization images. We focus on three types of road surfaces— asphalt, concrete, and metal—and classify them into dry, wet, and frozen states. Among the capture conditions, in particular, we examine how the positional relationship between the camera and the lighting influences the recognition of frozen road surface conditions. The results indicated that when the camera and lighting were aligned in the same direction, frozen conditions were successfully recognized on the asphalt surface. Conversely, when the camera and lighting were positioned in opposite directions, frozen conditions were observed on the concrete and metal surfaces. To evaluate the features used in image processing, we used a support vector machine to classify road surface images based on color and polarization information. The results demonstrate successful classification of images into frozen and wet/dry states. In this study, we clarified the appropriate capture conditions and features for frozen condition recognition based on the relationship between frozen road surface conditions and polarization characteristics, as well as the classification outcomes using these features.**

I. Introduction

Recognizing frozen road surface conditions—dry, wet, or frozen—is crucial for alerting drivers, providing road traffic information, guiding road managers in the application of antifreezing agents, and activating antislip devices. This study focuses on recognizing these frozen conditions.

Conventional methods for recognizing frozen road surface conditions typically involve using near-infrared laser sensors that measure the surface temperature, friction coefficient, and scattered light intensity [1], [2]. Other methods use ultrasonic sensors to measure the intensity of reflected ultrasonic waves, which helps to detect frozen conditions [3], [4]. Although effective, these conventional methods rely on point measurements, which means that they are localized and require multiple measurements to cover a certain area.

Several methods have been proposed for recognizing frozen road surface conditions using image processing techniques. Unlike point measurements, images with two-dimensional coverage allow frozen condition recognition across a certain area at once. However, using RGB cameras to capture road surface images presents challenges, particularly during twilight, nighttime, or dusk, due to considerable brightness changes. To address this issue, polarization cameras, which capture both brightness and polarization information, have been used. Notably, low lighting conditions do not influence polarization images, improving image recognition accuracy in such environments [5].

In addition, methods have been developed to process the polarization images captured by these cameras to recognize frozen road surface conditions. These studies, as detailed in Section 2, demonstrate the effectiveness of polarization images in terms of recognizing frozen conditions.

The polarization information extracted from the polarization images is influenced by the capture conditions, particularly the positional relationship between the camera and lighting, as well as the material of the object being imaged. Additionally, when selecting features for frozen condition recognition from RGB and polarization images, it is crucial to select the most suitable features for each lighting condition and road surface material. Previous studies have not fully addressed these aspects.

The objective of this study is to identify the optimal lighting conditions and features for recognizing frozen road surface conditions using polarization images.

The remainder of this study is organized as follows. Section 2 reviews related research in the area, and Section 3 outlines the study's assumptions . In Section 4, we investigate the capture conditions suitable for recognizing road surface frozen conditions. Section 5 examines the features optimal for frozen condition recognition. Based on these investigations, Section 6 discusses the applicability of the proposed method. Finally, Section 7 summarizes the main contributions of the study.

II. Related Works

This section reviews research on recognizing frozen road surface conditions using image processing.

Yamada *et al.* proposed a method for recognizing five types of road surface conditions—dry, wet, wet mixed with snow, frozen, and snow-covered—by detecting moisture using a polarization filter–equipped camera installed at a fixed point on the roadside [6]. They also extended their approach to recognize road surface conditions in a driving environment by mounting polarization filter–equipped camera on the vehicle's rearview mirror to capture the forward view [7].

Nguyen *et al.* developed a method for recognizing frozen road surface conditions using images captured by a polarization camera, specifically at night and under adverse weather conditions [8]. Their method involved color and

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polarization information extraction from road surface images for use as features to recognize frozen conditions. A Gaussian mixture model is used for classification.

These studies highlight the effectiveness of using polarization images for recognizing frozen road surface conditions. However, they also emphasize that the polarization characteristics are strongly influenced by lighting conditions and reflective properties of the surface material. Notably, these studies assumed that the camera and lighting sources were aligned in the same direction, and they primarily examined asphalt surfaces, which considerably influenced the reflectivity.

Therefore, it is crucial to investigate scenarios in which the camera and lighting are positioned in opposite directions, as well as scenarios including road surface materials other than asphalt.

With rapid advancements in deep learning (DL) technology by 2024, numerous applications have emerged for recognizing frozen road surface conditions. Pun *et al.* introduced a method using convolutional neural networks (CNNs) to recognize winter road surface conditions using images captured by smartphones [9]. Their study focused on dry, wet, and snow-covered surfaces. Similarly, Zhang *et al.* developed another CNN-based method to recognize winter road surface conditions using the RGB and thermal images [10]. The investigated frozen conditions were wet, frozen, snow-covered, and wet mixed with snow surfaces. They created a comprehensive dataset by combining the RGB and thermal images of various road surfaces and used this dataset to train a CNN model.

DL can recognize frozen road surface conditions. If a large, diverse image dataset that accounts for variations in appearances due to lighting changes and different frozen conditions can be created, the performance of frozen road surface recognition conditions could be considerably improved.

Our research group has also been actively exploring DL-based methods to identify frozen road surfaces. To achieve this, we utilized images captured by closed-circuit television (CCTV) cameras installed along national roads in Japan. An anomaly detection method was implemented, alongside a proposed automatic construction method for generating suitable training datasets tailored to each CCTV camera. The effectiveness of this approach has been successfully demonstrated.

However, despite these advancements, the specific factors contributing to improved performance in identifying frozen road surfaces remain unclear. This lack of clarity makes it challenging to assess the influence of lighting conditions and road surface materials.

Therefore, in this study, we deliberately employ a conventional machine learning method, support vector machine (SVM), that allows us to classify and systematically examine the influence of key factors such as lighting conditions, road surface materials, and the features used in the classification process.

III. Preliminaries

The polarization information obtained from a polarization camera is influenced the lighting conditions during image capture. To recognize the frozen condition of a road surface using polarization images, it is crucial to investigate how polarization information varies under different lighting conditions. Therefore, this study examines the correlation between frozen conditions and polarization information under specific lighting conditions. Based on the findings of this examination, ML is employed to classify and recognize the frozen conditions of the road surface.

This section provides a foundational overview necessary for conducting these experiments. It includes details on the methods used to acquire polarization images, the lighting conditions under consideration, and the features selected for validation.

A. Acquisition of the Polarization Images

Polarization refers to light vibrating within a specific plane, as opposed to ordinary light, which vibrates in random directions. A polarization camera captures the polarization information by exploiting the polarized light properties. The camera's sensor is equipped with polarizers oriented at 0°, 45°, 90°, and 135°. By capturing polarization data at each of these angles and calculating the degree of linear polarization (DoLP) using (1)–(4), a DoLP image is generated, indicating the level of polarization for each pixel [4].

$$S_0 = \frac{I_0 + I_{45} + I_{90} + I_{135}}{2} \tag{1}$$

$$S_1 = I_0 - I_{90} \tag{2}$$

$$S_2 = I_{45} - I_{135} \tag{3}$$

$$DoLP = \frac{\left(\sqrt{{S_1}^2 + {S_2}^2}\right)}{S_0} \tag{4}$$

In these equations, I_0, I_{45}, I_{90}, and I_{135} indicate the intensities of the polarized light at specific angles, while S refers to the Stokes parameters. The luminance values corresponding to the polarizer rotation angles of the camera are expected to follow a sinusoidal pattern. This sinusoidal wave can be estimated using the luminance values captured at the four orientations during a single capture. The maximum value of the estimated sine wave represents the specular reflection component I_{max}, whereas the minimum value corresponds to the diffuse reflection component I_{min}. The difference between these values yields the specular reflection image.

B. Simulated Road Surface

To validate the road surface polarization images, controlling the lighting conditions, including the light source, is essential. In addition, capturing frozen road surface images in natural environments is restricted to winter, which limits year-round experimentation. To address these seasonal constraints, simulated road surface were used as experimental targets.

Three representative road surface materials were selected for the experiments: asphalt, concrete, and metal. As shown in Figure 1, three types of plates were prepared for this purpose: asphalt plates (asphalt solidified into a plate-like form), concrete plates, and metal plates.

The primary road surface conditions—dry, wet, and frozen—were simulated as follows. The dry condition was represented by untreated boards, the wet condition was reproduced by spraying water onto the board surfaces, and the frozen condition was achieved by freezing the water-sprayed boards in a freezer. To minimize external influences, the road surfaces were photographed in a darkroom so that lighting conditions could be precisely controlled.

C. *Lighting Conditions*

The polarization parameters obtained by the polarization camera depend on the lighting conditions. The relative positions of the lighting, camera, and simulated road surface being imaged may affect these polarization parameters.

To examine the influence of the positional relationship between the camera and lighting on frozen condition recognition, two lighting conditions were established (Fig. 2). These conditions were tested for each of the three material types and frozen conditions, as mentioned earlier. Lighting Condition I: involves the polarization camera and lighting being positioned in opposite directions. Lighting Condition II involves the polarization camera and lighting being position in the same direction. For both conditions, the height of the polarization camera, distance between the camera and road surface, and distance between the lighting and road surface were all set to 0.50 m. These parameters were selected assuming that a polarization camera was mounted on a vehicle to capture road surface images.

A color polarization camera (VP-PHX050S-Q, LUCID) with a 50-mm fixed focal length lens (M112FM12, TAMRON) was used to capture the images. The illumination was provided by a lighting device (LG-E268C, LEDGO), which maintained a consistent illuminance level between 760 and 800 lux under both lighting conditions.

D. *Features*

To identify the most relevant features for recognizing frozen road conditions using polarization images, six specific features were selected for analysis. These include: the average values of each HSV component per pixel, the average and variance values of DoLP, and the average value of the specular reflectance.

An overview of the feature extraction process is shown in Fig. 3. The HSV values were obtained from RGB images, while the DoLP and specular reflectance were derived from DoLP images and specular reflection images, respectively. Since calculating the variance of DoLP on a per-pixel basis is

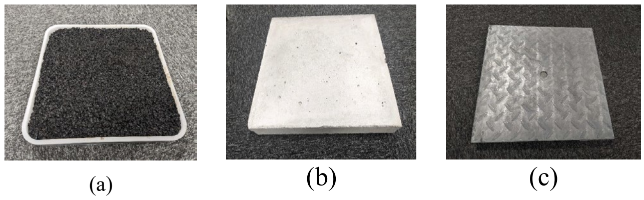


Figure 1. Examples of (a) asphalt, (b) concrete, and (c) metal simulated road surfaces

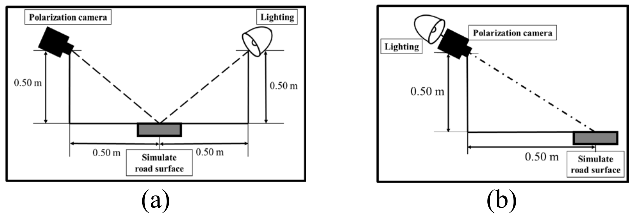


Figure 2. Diagram of (a) Lighting Condition I and (b) Lighting Condition II

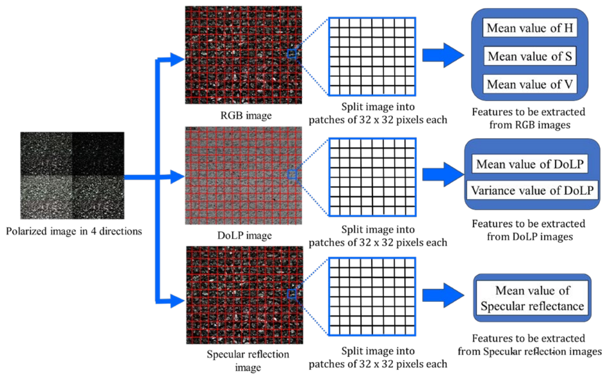


Figure 3. Feature extraction process

not feasible, each image was divided into smaller patches with a pixel size of 32 × 32. For each of these patches, all six types of features are calculated.

IV. Investigation of the Relationship Between Road Surface Frozen Conditions and Lighting Conditions

This section examines the relationship between road surface frozen conditions and lighting conditions, using box plots based on the DoLP images of the road surfaces. DoLP values are extracted from each captured DoLP image, and box plots are generated to visualize the data. The vertical axis of each box plot represents the DoLP values, displaying the maximum, minimum, first quartile, third quartile, median, and mean. By analyzing the DoLP distributions from each image, we investigated the potential to recognize frozen conditions of road surfaces, considering the material type, frozen state, and lighting conditions.

Fig. 4 illustrates teh DoLP distributions under Lighting Condition I and Lighting Condition II. For each road surface material and frozen state, box plots are presented. Beneath each box plot, the corresponding DoLP images used for generating the box plots are shown. To enhance visibility, the

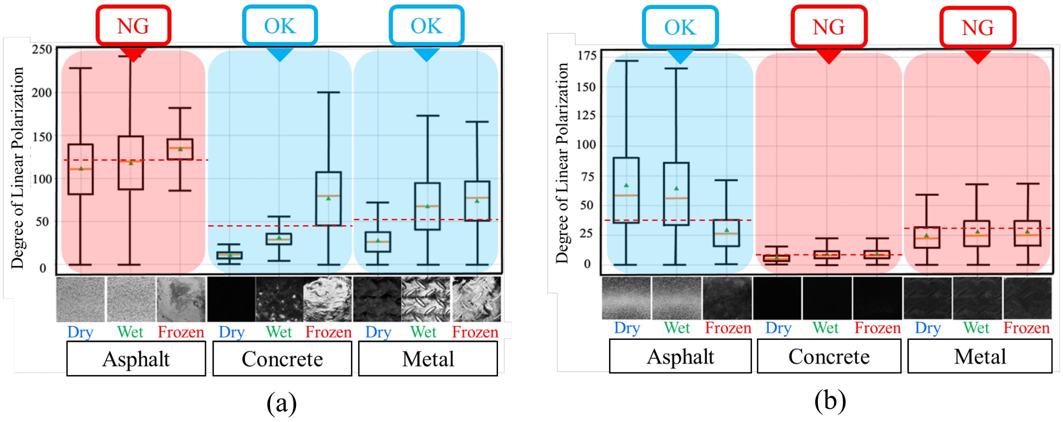


Figure 4. Box plots of DoLP generated from road surface images under (a) Lighting Condition I and (b) Lighting Condition II

brightness and contrast of these images were adjusted We compared the median and mean DoLP obtained values obtained from the distributions under both lighting conditions.

The DoLP distributions under Lighting Condition I revealed that the concrete road surface exhibited differences in distribution for various frozen conditions. Similarly, the metal road surface exhibited notable differences among the dry and wet/frozen states. However, the asphalt road surface did not display noticeable differences across the frozen conditions. Under Lighting Condition II, no significant differences were observed in the DoLP distributions for the concrete and metal road surfaces; however, the asphalt road surface showed distinct differences between the dry/wet and frozen conditions.

These findings suggest that frozen condition recognition is more effective for asphalt when the camera and lighting are aligned in the same direction. On the other hand, recognition is more feasible for concrete and metal surfaces when the camera and lighting are positioned oppositely.

V. FROZEN CONDITION RECOGNITION OF ROAD SURFACES USING SVM

In this section, we recognize the frozen conditions of road surfaces—dry, wet, and frozen—using road surface images captured from asphalt, concrete, and metal surfaces.

A. *Method of Frozen Conditions Recognition*

The frozen condition recognition classifier employs SVM. A key advantage of using SVM is the ability to manually design the features used for recognizing frozen conditions. We prepared combinations of the six feature types described in Section 3 and used SVM to classify the frozen and dry/wet conditions to identify the combination of features with the highest recognition accuracy for the frozen conditions.

For training, we prepared 30 images for each of the dry, wet, and frozen states across the three road surface materials. These training images included RGB, DoLP, and specular reflection images of each road surface under the various frozen conditions. Features used for SVM training and validation were extracted from three images per road surface.

Based on the analysis in Section 4 of the relationship between road surface frozen conditions and lighting conditions, datasets were created using road surface images captured under both appropriate and inappropriate lighting conditions for each road surface material. These datasets were then used for training and validating the SVM model for frozen condition recognition.

B. *Evaluation Method*

The evaluation of frozen condition recognition results from road surface images is based on the metrics of precision, recall, and F-score, as given by (5), (6), and (7), respectively.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

In these equations, TP, FP, and FN stand for true positive, false positive, and false negative, respectively. For each image patch in the validation dataset, the results of frozen state recognition are classified into four outcomes. A correct recognition of the frozen state by the SVM is defined as a TP, while a correct recognition of the wet or dry state is defined as a true negative (TN). Conversely, if the wet or dry state is mistakenly recognized as the frozen state, it is considered a FP, and if the frozen state is mistakenly recognized as the dry or wet state, it is classified as a FN. Table 1 presents these four outcomes in a 2 × 2 grid.

TABLE I. DEFINITION OF TRUE AND FALSE POSITIVES AND NEGATIVES

		Validation	
		Frozen	***Dry/Wet***
Correct	Frozen	TP	FN
	Dry/Wet	FP	TN

C. *Validation Results*

To evaluate the frozen condition recognition model, we trained an SVM using features extracted from images of three different materials. The model was validated using 30 frozen

TABLE II. RESULTS OF THE FROZEN CONDITION RECOGNITION OF THE ROAD SURFACE UNDER INAPPROPRIATE LIGHTING CONDITIONS FOR EACH MATERIAL

	Asphalt (Lighting Condition I)			**Concrete (Lighting Condition II)**			**Metal (Lighting Condition II)**		
Evaluation index / Feature	***Precision***	***Recall***	***F-score***	***Precision***	***Recall***	***F-score***	***Precision***	***Recall***	***F-score***
HSV	0.681	0.526	**0.594**	**0.501**	**0.475**	**0.488**	0.430	0.224	**0.461**
P	0.489	0.494	0.492	0.249	0.152	0.189	0.229	0.150	0.155
I	0.188	0.421	0.260	0.281	0.199	0.233	0.198	0.146	0.169
HSV+P	**0.651**	**0.531**	**0.585**	**0.502**	0.243	0.327	**0.436**	0.203	0.295
HSV+I	0.323	**0.613**	0.423	0.230	**0.392**	0.290	0.360	**0.253**	0.297
HSV+P+I	**0.667**	0.500	0.571	0.497	0.225	**0.337**	0.411	**0.259**	**0.318**

TABLE III. RESULTS OF THE FROZEN CONDITION RECOGNITION OF THE ROAD SURFACE UNDER APPROPRIATE LIGHTING CONDITIONS FOR EACH MATERIAL

	Asphalt (Lighting Condition II)			**Concrete (Lighting Condition I)**			**Metal (Lighting Condition I)**		
Evaluation index / Feature	***Precision***	***Recall***	***F-score***	***Precision***	***Recall***	***F-score***	***Precision***	***Recall***	***F-score***
HSV	0.726	0.519	0.605	0.538	0.499	0.518	0.455	**0.645**	**0.533**
P	0.635	0.522	0.573	0.474	0.327	0.387	0.326	**0.968**	0.488
I	0.269	0.519	0.354	0.571	0.686	0.623	0.428	0.376	0.394
HSV+P	0.792	0.683	0.733	**0.839**	**0.692**	**0.758**	**0.633**	0.499	**0.558**
HSV+I	**0.826**	**0.712**	**0.765**	**0.720**	0.708	**0.714**	**0.631**	0.429	0.511
HSV+P+I	**0.841**	**0.750**	**0.793**	0.691	**0.709**	0.700	0.627	0.441	0.525

and 15 wet and 15 dry surface images for each material. The recognition results for road surface images captured under inappropriate and appropriate lighting conditions are summarized in Tables 2 and 3, respectively. In addition, Table 4 presents a detailed breakdown of the feature combinations used. In Table 2, the highest value for each a material across the evaluation metrics is highlighted in bold with shading, and the second-highest value is also shown in bold for comparison.

We compared the F-score for different road surface materials and features based on the results presented in Tables 2 and 3. Precision measures the correctly identified frozen image patches proportion among those classified as frozen, and recall reflects the correctly classified frozen image patch proportion out of all actual frozen patches. The F-score—the harmonic mean of precision and recall—is particularly relevant in this context because it balances the need to avoid misclassifying frozen conditions and the need to correctly identify all actual frozen conditions.

A comparison of the results presented in Tables 2 and 3 highlights the notable improvement in classification performance when appropriate lighting conditions, as discussed in Section 4, are applied to each road surface material. Specifically, the precision metrics for polarization features, such as the degree of polarization and specular reflectance, indicate that improper lighting conditions impede the effective extraction of critical features from polarization images, which are critical for accurate road surface condition recognition.

A detailed examination of Table 3 reveals that for all road surface materials, incorporating polarization features—such as the degree of polarization and specular reflectance—results in higher F-scores than using only HSV color information. This observation highlights the effectiveness of polarization features in frozen road surface condition recognition.

TABLE IV. FEATURE COMBINATIONS

Feature	Feature Components
HSV	Mean values of H,S,V
P	Mean and variance of the DoLP
I	Mean value of the specular reflectance
HSV+P	Combination of HSV and P
HSV+I	Combination of HSV and I
HSV+P+I	Combination of HSV, P, and I

In conclusion, the results indicate that frozen road surface condition recognition is achievable by classifying image patches into frozen and wet/dry states using an SVM classifier. This classifier utilizes a combination of features extracted from both color and polarization information and is thus an effective classification method.

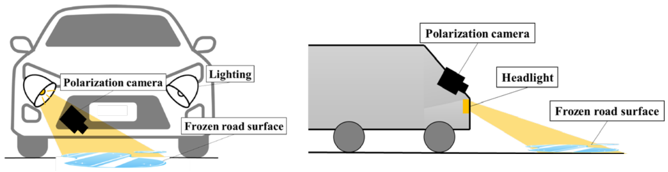
VI. APPLICABILITY OF THE PROPOSED METHOD

The applicability of the method proposed in this study is examined in the context of recognizing road surface conditions using a polarization camera mounted on a vehicle.

Fig. 5 illustrates two scenarios in which a polarization camera is mounted on a vehicle. In Scenario I, the vehicle is equipped with a polarization camera and two light sources. These lights are positioned to project light both opposite to and in the same direction as the camera's field of view, allowing the camera to capture images of the road directly beneath the vehicle. In Scenario II, the vehicle's headlights serve as the light source, and the camera captures images of the road ahead. During operation, polarization data obtained from these captured images is used to identify the frozen condition of the road surface.

In Scenario I, both Lighting Condition I and Lighting Condition II from this study can be effectively applied. This setup enables the recognition of frozen road conditions on surfaces made of asphalt, concrete, and metal. However, as the camera focuses solely on the road directly beneath the vehicle, the vehicle's forward view is not captured. Therefore, it is anticipated that the road condition information, such as the detection of frozen surfaces, would be shared with other vehicles, possibly through vehicle-to-vehicle communication, to alert and inform following vehicles.

Meanwhile, in Scenario II, securing a stable light source opposite the camera poses a challenge. With the vehicle's headlights serving as the sole light source, this setup aligns with Lighting Condition II from the study. Consequently, the recognition is limited to asphalt surfaces; however, identifying frozen conditions remains feasible. Additionally, since the camera captures the road ahead, this road surface information can be utilized not only for sharing with other vehicles but also by the vehicle itself.



(a) Senario I (b) Senario II

Figure 5. Practical application scenarios of the proposed method: (a) Scenario I (Capturing the area directly beneath the vehicle) and (b) Scenario II (Capturing the vehicle's forward view)

VII. CONCLUSION

We successfully investigated optimal lighting conditions and features required to recognize frozen road surface conditions.

Regarding lighting conditions, the DoLP distribution of road surfaces was examined under two configurations: (1) when the camera and lighting were positioned in the same direction, and (2) when they were position in opposite direction. When the camera and lighting were aligned in the same direction, the DoLP distribution exhibited notable differences between the dry/wet and frozen states on asphalt surfaces. Conversely, when the camera and lighting were positioned in opposite direction, the DoLP distribution revealed differences between frozen states on concrete surfaces and between dry and wet/frozen states on metal surfaces.

Concerning features, the frozen road surface conditions were classified using SVM trained with images captured under the optimized lighting conditions for each material. The results demonstrate improved classification accuracy when combining color and polarization information, which demonstrates the importance of integrating these features.

In conclusion, this study suggests that frozen conditions on asphalt, concrete, and metal surfaces can be effectively recognized using polarization images, offering practical implications for road safety and monitoring systems.

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