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# Vision-based black ice identification using lightweight CNN and CLAHE-enhanced imagery

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ABSTRACT

This paper presents BlackNet, a vision-based black ice detection system designed for real-time vehicular safety. Unlike traditional methods that require expensive environmental sensors, BlackNet leverages existing onboard surround-view cameras. The proposed architecture integrates ResNet-style residual connections into a lightweight MobileNetV2 backbone to optimize feature extraction for subtle road surface variations. To enhance visibility in low-light and high-glare conditions, Contrast Limited Adaptive Histogram Equalization (CLAHE) is utilized for image preprocessing. The model was trained and validated on a comprehensive dataset of 15,200 images, achieving an accuracy of 92.4%. We propose a cloud-assisted deployment framework where inference is performed remotely in cloud, overcoming the computational constraints of edge devices. This approach offers a scalable, hardware-efficient solution for autonomous and connected vehicle safety.

## 1. Introduction

Traditional black ice detection methods primarily rely on environmental sensors, such as temperature and humidity sensors, installed on roads or vehicles [1]. While these sensor-based approaches provide useful data, they suffer from limitations, including delayed detection, high installation and maintenance costs, and susceptibility to environmental degradation over time. Additionally, methods like infrared thermography and laser-induced spectroscopy [2] offer improved accuracy but require expensive equipment, making them impractical for large-scale deployment. As a result, there is a need for a cost-effective, scalable, and real-time black ice detection system that can be integrated into modern vehicles without significant hardware modifications [3].

With advancements in computer vision and deep learning, Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in road condition monitoring [4,5]. CNNs are capable of automatically learning and extracting relevant features from images, making them an effective tool for black ice detection. However, real-time deployment in vehicular environments presents challenges related to computational efficiency, model inference latency, and data transmission speed [6]. To address these challenges, lightweight deep learning models such as MobileNetV2 have gained traction due to their reduced computational complexity while maintaining competitive accuracy.

In this paper, we introduce BlackNet, a vision-based black ice detection system designed to enhance road safety by leveraging a modified MobileNetV2 architecture. Unlike conventional MobileNetV2 implementations, BlackNet integrates ResNet-style long-range residual connections to improve feature extraction and gradient propagation. This architectural enhancement not only facilitates better training dynamics but also ensures robust performance across diverse environmental conditions. The overall architecture of the proposed BlackNet system is depicted in Fig. 1. The system utilizes open-source datasets containing real-world road condition images [7], including dry, wet, snowy, and black ice scenarios. Additionally, we apply Contrast Limited Adaptive Histogram Equalization (CLAHE) as a preprocessing technique to improve visibility of black ice in low-light or high-glare conditions.

The primary contributions of this paper are as follows:

1. **Development of BlackNet**, a CNN-based vision model that introduces residual connections to MobileNetV2 for improved feature extraction, leading to enhanced black ice detection accuracy.
2. **Comprehensive dataset curation and augmentation**, incorporating diverse road conditions to improve generalization and model robustness.

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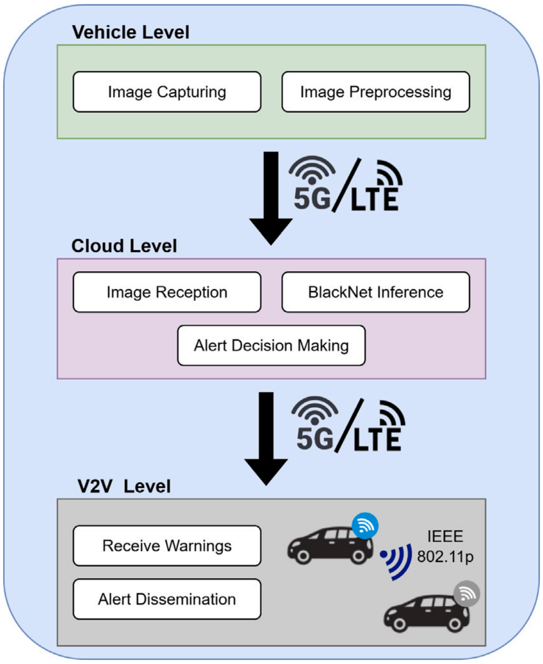


**Fig. 1.** Overview of the proposed BlackNet system. The vehicle-mounted camera captures road surface images, processes them locally, and transmits them to the cloud for classification. If black ice is detected, a warning is sent to connected vehicles.

This paper is structured as follows: In Section 2, we review the existing literature relevant to our study. Section 3 provides details about the dataset used. Our proposed model is described in Section 4,. Section 6 presents the results and discussion. Finally, Section 8 concludes the paper with key findings.

## 2. Related works

Lee et al. presents a method to detect black ice on roads using Convolutional Neural Networks (CNN) to prevent accidents in automated vehicles. The authors collected image data from various environments and augmented it to create a comprehensive dataset. They used grayscale images of road environments and trained a CNN model, achieving 96% accuracy in black ice detection [8]. Abdalla et al. proposed a black ice detection system using a depth imaging sensor based on the Kinect device. The system classifies different types of ice (soft ice, wet snow, hard ice, black ice) and measures ice thickness and volume. It operates within a range of 82 cm to 1.52 m from the camera. The system was tested on various backgrounds such as wood, glass, ceramic, plastic, and concrete, demonstrating high proficiency in detecting black ice by utilizing Kinect's depth-sensing capabilities [9]. Ma et al. focuses on using a tri-wavelength non-contact optical technology to detect black ice. The method distinguishes dry, wet, black ice, ice, and snowy conditions by measuring the reflectance at three different wavelengths (1310 nm, 1430 nm, 1550 nm). The study confirmed the effectiveness of this approach in detecting black ice through wavelength-specific reflectance patterns, suggesting its potential application in developing advanced equipment for road condition monitoring [2].

Najafi et al. proposed a low-power black ice detection approach for safety-critical edge devices on roads. Their method utilizes CCTV systems combined with Convolutional Neural Networks (CNN) to calculate sharpness and glossiness factors, enhancing detection performance while optimizing resource utilization. They introduced a novel "Black Ice Factor" to process road surface characteristics, achieving 98.6% precision with a processing time of 10.8 ms per frame on edge devices [10]. Kim et al. presented a black ice detection method using mmWave sensors and a 1D Convolutional Neural Network (CNN). Their system processes Frequency Modulated Continuous Wave (FMCW) backscattering data to identify black ice irrespective of lighting conditions. Experimental results demonstrated high accuracy, achieving 95.6% in low-light environments and 98.5% under sunlight, showcasing robustness compared to traditional optical or IR sensor-based methods [11].

Bhattacharyya et al. propose a novel approach for classifying black ice using hyperspectral imaging combined with a 2D–3D convolutional neural network (CNN). Unlike traditional methods relying on RGB images or sensor-based approaches, this work utilizes hyperspectral data to extract rich spectral and spatial features, enabling more accurate ice classification. Principal Component Analysis (PCA) is employed for dimensionality reduction, improving computational efficiency. The model demonstrates superior performance with an overall accuracy a 10-meter distance and robustness up to 30 m, significantly outperforming existing RGB-based and hyperspectral classification techniques [12].

Unlike previous methods that rely on expensive specialized sensors like depth or mmWave devices, BlackNet utilizes existing onboard vehicle cameras to provide a cost-effective safety solution. Architecturally, it improves upon standard models by integrating ResNet-style residual connections into a MobileNetV2 backbone, enhancing feature extraction for subtle road variations. Furthermore, the addition of CLAHE preprocessing specifically targets the visual confusion between black ice and wet roads, achieving high accuracy without requiring additional hardware.

**Table 1**
Dataset composition and image count.

| Category | Number of images |
|---|---|
| Dry Road | 4500 |
| Wet Road | 3800 |
| Snowy Road | 4200 |
| Black Ice | 2700 |
| Total | **15,200** |

## 3. Dataset description

This dataset include images categorized into four distinct classes: dry, wet, snowy, and black ice. The diverse range of environmental conditions captured within these datasets ensures that the model is robust across different scenarios.

### *3.1. Dataset source and composition*

The dataset used in this study was curated from publicly accessible repositories specializing in road condition monitoring [7]. The images were collected from multiple sources, such as, Traffic monitoring systems, Dashcam footage, and Crowdsourced images. But we made sure to choose only images that point in the direction that aligns with our approach. To quantify the dataset composition, Table 1 lists the number of images in each category.

### *3.2. Contrast Limited Adaptive Histogram Equalization (CLAHE)*

On top of the common data augmentation methods used for model training we applied CLAHE to improve local contrast and highlight road surface textures, particularly beneficial for distinguishing subtle features such as black ice patches under poor lighting or glare. The application of CLAHE is crucial in this context, as black ice tends to visually blend with wet asphalt, especially in dim or highly reflective conditions. Enhanced local contrast helps the CNN model identify subtle surface irregularities that are otherwise indistinguishable [13].

**Fig. 2.** Sample images from the dataset: Wet road, Dry road, Black ice and Snowy road, respectively.

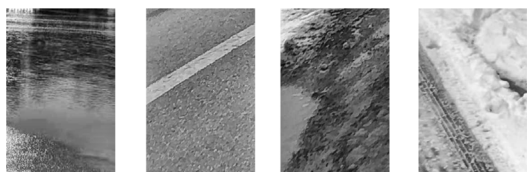

**Fig. 3.** Sample images after using CLAHE.

### 3.3. Sample images

Fig. 2 provides examples of images from each category, illustrating the visual challenges associated with black ice detection. These examples underscore the necessity of a robust and carefully designed CNN architecture, as well as proper preprocessing strategies.

Applying CLAHE to an input image enhances its contrast while preventing over-amplification of noise. Fig. 3 shows the samples after CLAHE.

### 3.4. Evaluation in challenging scenarios

A major concern in black ice detection is its visual similarity to wet road surfaces, which can lead to misclassification. To address this challenge, we tested the model's robustness in three specific scenarios:

- Low-light conditions: Images captured at night or under foggy weather.
- High-glare conditions: Roads affected by excessive sunlight reflections.
- Mixed-surface conditions: Roads with both wet and black ice patches.

To quantitatively evaluate performance in these scenarios, we curated an additional 500 test images per condition and measured class-wise accuracy, as reported in the results section.

These augmentations ensure the model is exposed to a wide range of environmental conditions and visual variations during training.

## 4. Proposed model

In this section, we present the architecture and workflow of the proposed vision-based black ice detection system, BlackNet. The model leverages a modified MobileNetV2 architecture enhanced with ResNet-style residual connections to improve feature extraction and gradient flow [14]. The design ensures efficient performance for real-time detection, making it suitable for deployment on vehicles equipped with onboard cameras and low-latency communication technologies.

### 4.1. Architecture overview

The core architecture of BlackNet is based on MobileNetV2, which is known for its lightweight and efficient structure [15]. We enhance this architecture by incorporating long-range residual connections inspired by ResNet [16]. These connections improve gradient propagation and feature reuse, enabling the model to achieve better performance without significantly increasing computational complexity [17].

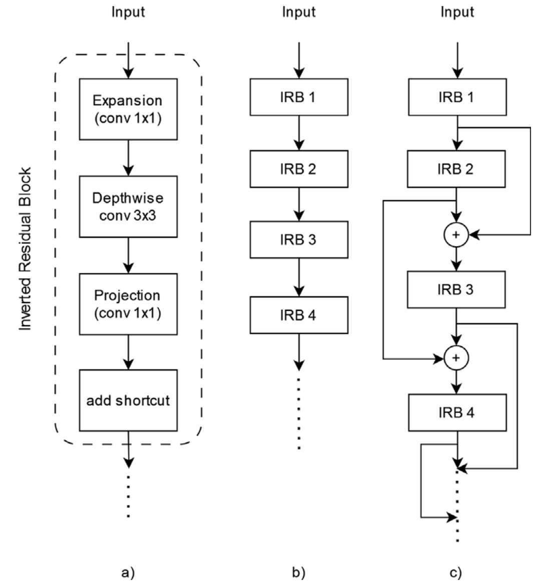


**Fig. 4.** (a) Inverted residual block architecture, (b) Traditional MobileNetV2, and (c) Proposed BlackNet with ResNet-style residual connections.

The modified MobileNetV2 backbone in BlackNet ensures a balance between computational efficiency and model accuracy, as illustrated in Fig. 4.

#### 4.1.1. Inverted residual blocks with residual connections

The Inverted Residual Block in MobileNetV2 applies a series of transformations that reduce the computational cost while maintaining high accuracy. The forward pass through the inverted residual block is formulated as follows:

For linear Expansion, The input tensor $X$ is first passed through a $1\times1$ convolution (linear expansion) to increase the number of channels:

$$X_1 = \sigma(W_{1x1} * X), \tag{1}$$

where: $W_{1x1}$ is the $1\times1$ convolution filter used for expansion, increasing the number of channels. $\sigma$ represents the ReLU6 activation function, which ensures that negative values are set to zero and limits the upper bound to 6.

Next, a depthwise convolution is applied to the expanded tensor $X_1$:

$$X_2 = \sigma(W_{dw} * X_1), \tag{2}$$

where: $W_{dw}$ is the depthwise convolution filter, applied to each channel separately. $X_1$ is the input to the depthwise convolution, and $X_2$ is the output after the convolution.

A pointwise $1 \times 1$ convolution is applied to reduce the number of channels back down:

$$X_3 = \sigma(W_{pw} * X_2), \tag{3}$$

where: $W_{pw}$ is the pointwise convolution filter. $X_2$ is the output of the depthwise convolution. $X_3$ is the output of the pointwise convolution.

The residual connection is added to facilitate better gradient flow and mitigate the vanishing gradient problem. The residual connection is formulated as:

$$Y = F(X) + X, \tag{4}$$

where: $F(X)$ represents the output from the series of transformations, $X_3$, which consists of the expansion, depthwise, and pointwise convolutions. $X$ is the original input tensor. $Y$ is the final output of the residual block, which is added to the original input tensor $X$.

**Table 2**
Hyperparameter configuration for BlackNet training.

| Hyperparameter | Value |
|---|---|
| Initial Learning Rate | 0.001 |
| Learning Rate Decay | 0.1 (every 10 epochs if validation loss stagnates) |
| Batch Size | 32 |
| Number of Epochs | 50 |
| Optimizer | Adam |
| Loss Function | Categorical Crossentropy |
| Weight Initialization | He Normal |
| Early Stopping Patience | 5 epochs |
| Regularization | L2 weight decay ($10^{-5}$) |

**Table 3**
Comparison of model complexity.

| Model | Parameter count | FLOPs (GMac) |
|---|---|---|
| ResNet-50 | 25.6M | 4.1 |
| VGG-19 | 143M | 19.6 |
| MobileNetV2 | 3.4M | 0.3 |
| BlackNet (Proposed) | **3.9M** | **0.35** |

The residual connection ensures that the network can learn more complex features without losing critical information through the layers. This is particularly useful for preventing the vanishing gradient problem and ensuring that deeper layers can be effectively trained.

## 5. Model training and optimization configuration

The proposed BlackNet model was trained and optimized using well-established deep learning techniques to ensure high accuracy and robust performance under various road conditions. This section outlines the training configuration, including hardware setup, learning rate scheduling, data augmentation, and performance monitoring. The model was evaluated using a robust 70% training, 20% for validation and 10% testing split. While k-fold cross-validation was not applied in this version due to the specific data structure.

### 5.1. Hyperparameter configuration

The training process was optimized using the Adam optimizer with adaptive learning rates. The key hyperparameters are listed in Table 2.

### 5.2. Model complexity and parameter count

One of the key advantages of BlackNet is its efficiency in terms of model size and computational requirements. Table 3 compares the parameter count and FLOPs of BlackNet with existing models.

### 5.3. Advantages of the modified architecture

The proposed BlackNet architecture offers several advantages:

- **Improved Gradient Flow**: The ResNet-style connections facilitate better gradient propagation, reducing the risk of vanishing gradients.
- **Lightweight Design**: The use of MobileNetV2 ensures the model remains efficient, suitable for real-time applications.
- **Robust Detection**: The combination of depthwise convolutions and residual connections improves performance, particularly under challenging conditions.

By incorporating these design elements, BlackNet offers a robust, scalable, and efficient solution for vision-based black ice detection, ensuring that the system performs reliably even in diverse environmental conditions.

**Table 4**
Performance metrics for BlackNet on the test set.

| Class | Precision | Recall | F1-score | Accuracy |
|---|---|---|---|---|
| Dry Road | 94.2% | 94.8% | 94.5% | 93.9% |
| Wet Road | 92.6% | 91.8% | 92.2% | 91.4% |
| Snowy Road | 95.1% | 95.3% | 95.2% | 94.7% |
| Black Ice | 90.8% | 89.6% | 90.2% | 89.1% |
| Average | **93.2%** | **92.9%** | **93.0%** | **92.4%** |

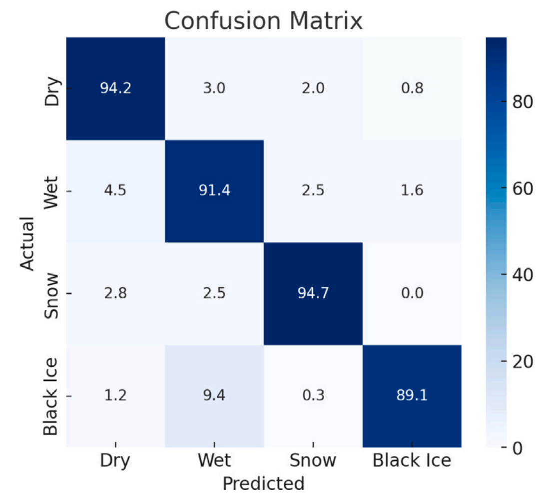


**Fig. 5.** Confusion matrix of BlackNet's classification results.

## 6. Simulation results

This section presents the experimental results of the proposed BlackNet model, evaluating its classification performance, and robustness under challenging conditions. We analyze key metrics such as accuracy, precision, recall, and F1-score, followed by discussions on confusion patterns and model comparisons.

### 6.1. Overall performance

The performance of BlackNet was evaluated on the test dataset, consisting of 1520 images across four categories: Dry, Wet, Snow, and Black Ice. The classification results are summarized in Table 4.

The results indicate that BlackNet achieves an overall accuracy of 92.4%, with the highest performance observed in the Snowy Road class. The Black Ice class has the lowest accuracy due to its visual similarity to wet roads.

### 6.2. Confusion matrix analysis

The confusion matrix in Fig. 5 provides insight into class-wise misclassifications.

The majority of errors occur between Black Ice and Wet Road, where 9.4% of black ice samples were misclassified as wet road. This confusion is expected due to the similar reflectance characteristics and visual appearance of these surfaces [18]. To mitigate the 9.4% misclassification rate between black ice and wet roads, future iterations could incorporate lightweight attention mechanisms to focus on region-specific surface textures or utilize multi-spectral fusion as suggested in recent safety frameworks.

### 6.3. Performance in challenging scenarios

To further evaluate BlackNet's robustness, we tested it on 1500 additional images captured under challenging conditions: low-light

**Table 5**
Performance in challenging scenarios.

| Scenario | Accuracy | F1-score |
|---|---|---|
| Normal Conditions | 92.4% | 93.0% |
| Low-Light Conditions | 88.1% | 88.4% |
| High-Glare Surfaces | 85.7% | 85.9% |
| Mixed-Surface Conditions | 82.3% | 83.1% |

**Table 6**
Comparison with existing black ice detection methods.

| Method | Accuracy | Hardware | Inference time (ms) |
|---|---|---|---|
| Image-Based [8] | 85.6% | Camera | 170 ms |
| Kinect-Based [9] | 92.0% | Depth Sensor | 330 ms |
| CNN-Based [10] | 91.5% | Edge Device + CCTV | 140 ms |
| BlackNet (Proposed) | **92.4%** | Standard Camera | **85 ms** |

**Table 7**
Comparison with other deep learning models.

| Model | Accuracy (%) |
|---|---|
| GoogLeNet [19] | 83.48 |
| VGG-19 [20] | 86.62 |
| ResNet-18 [16] | 88.94 |
| DarkNet-19 [21] | 90.07 |
| ResNet-50 [16] | 90.12 |
| MobileNetV2 [15] | 90.85 |
| BlackNet (Proposed) | **92.4** |

environments, high-glare surfaces, and mixed-surface conditions. Table 5 shows the performance degradation under these scenarios.

Performance degradation is most noticeable in mixed-surface conditions, highlighting the challenge of detecting black ice when it coexists with wet or snowy regions.

### 6.4. Comparison with existing black ice detection methods

We compared BlackNet against prior black ice detection techniques, as shown in Table 6.

BlackNet outperforms previous methods in accuracy and achieves significantly lower inference latency, making it well-suited for real-time vehicular deployment. Although [8] is using images only like our approach but their images are collected from scattered photos on the internet which does not show similar environment and background. In real life scenarios the images taken by the same car will show similarity in the images. As demonstrated in Table 6, BlackNet outperforms traditional Image-based and depth-sensing methods in both accuracy and latency. For instance, Image-based approach [8] is limited by a 170 ms latency and 85.6% accuracy, whereas BlackNet reduces inference time to 85 ms on a GPU. This improvement is critical for high-speed vehicular environments where millisecond delays impact safety. Also most of the other approaches do not use real-life image prospective.

### 6.5. Comparison with deep learning models

We also evaluated BlackNet against widely used deep CNN architectures trained on the same dataset. Table 7 shows that BlackNet achieves the highest accuracy among all tested models.

### 6.6. Impact of preprocessing: CLAHE evaluation

To assess the contribution of preprocessing, we evaluated the model with and without CLAHE. Table 8 shows that CLAHE improves accuracy significantly.

This highlights CLAHE's effectiveness in enhancing subtle features like black ice, particularly in poor lighting or high-glare environments.

**Table 8**
Impact of CLAHE on model performance.

| Model | Without CLAHE (%) | With CLAHE (%) |
|---|---|---|
| MobileNetV2 | 89.66 | 90.85 |
| BlackNet (Proposed) | 90.13 | 92.4 |

**Table 9**
Inference time across different hardware.

| Device | Inference time (ms) |
|---|---|
| NVIDIA RTX 3090 (GPU) | 85 |
| Intel Core i9-12900K (CPU) | 210 |
| Raspberry Pi 4 (Edge Device) | 410 |

### 6.7. Inference time analysis

To evaluate real-time feasibility, we measured BlackNet's inference time across different hardware platforms:

Table 9 highlights the significant performance disparity between cloud-grade hardware and resource-constrained edge devices. While GPU-based inference achieves low latency (85 ms) and CPU-based execution remains reasonably efficient (210 ms), inference on the Raspberry Pi 4 incurs a substantially higher delay of 410 ms. This result clearly indicates that edge devices are not well suited for executing the proposed model under real-time or near-real-time constraints due to their limited computational capabilities.

These findings strongly motivate a cloud-centric deployment strategy, where both training and inference are executed on powerful cloud infrastructure. By offloading computation from the edge to the cloud, the system can achieve low latency, stable performance, and scalability without sacrificing detection accuracy. Consequently, edge devices are better utilized for data collection and transmission rather than on-device model execution.

## 7. Discussion and future works

The results demonstrate that BlackNet provides high accuracy for black ice detection while maintaining low computational cost. However, some challenges remain:

- **Misclassification between Wet and Black Ice**: Due to visual similarities, distinguishing between these classes remains challenging.
- **Performance in Mixed Conditions**: Accuracy drops in scenarios with overlapping road surface types.
- **Edge Deployment Limitations**: Inference time is high on low-power devices; compression and optimization are required.

Future improvements will explore the integration of lightweight attention mechanisms to focus on region-specific surface textures or the use of multi-spectral data augmentation to emphasize discriminative features that are often indistinguishable in the RGB spectrum. Also, future work will have to discuss the privacy issues of this model by addressing approaches such as [22].

## 8. Conclusion

In this study, we developed and evaluated BlackNet, a lightweight CNN-based framework for identifying hazardous black ice using standard vehicle cameras. Our findings demonstrate that the inclusion of residual connections and CLAHE-enhanced imagery significantly improves detection accuracy to 92.4%, particularly in challenging lighting scenarios. The primary contributions of this work include: (1) a computationally efficient architecture that balances depth and speed, (2) a cloud-assisted real-time inference pipeline that bypasses edge-device limitations, and (3) a cost-effective safety mechanism that requires no additional sensors. While BlackNet achieves high overall performance, the 9.4% misclassification rate between black ice and wet roads remains a primary challenge due to similar reflectance.

## CRediT authorship contribution statement

**Ali Aouto:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Jung-Hyeon Kim:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Jae-Min Lee:** Validation, Supervision, Project administration. **Dong-Seong Kim:** Writing – review & editing, Supervision, Investigation, Funding acquisition.

## Declaration of competing interest

The authors certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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## References

[1] H. Tabatabai, M. Aljuboori, A novel concrete-based sensor for detection of ice and water on roads and bridges, Sensors 17 (12) (2017) http://dx.doi.org/10.3390/s17122912.

[2] X. Ma, C. Ruan, Method for black ice detection on roads using tri-wavelength backscattering measurements, Appl. Opt. 59 (24) (2020) 7242–7246, http://dx.doi.org/10.1364/AO.398772.

[3] S. Bhardwaj, D.-S. Kim, Federated learning-based joint radar-communication mmwave beamtracking with imperfect CSI for V2X communications, in: 2023 Fourteenth International Conference on Ubiquitous and Future Networks, ICUFN, 2023, pp. 201–206, http://dx.doi.org/10.1109/ICUFN57995.2023.10199843.

[4] H. Lee, M. Kang, J. Song, K. Hwang, The detection of black ice accidents for preventative automated vehicles using convolutional neural networks, Electronics 9 (12) (2020) http://dx.doi.org/10.3390/electronics9122178.

[5] M. Jakubec, E. Lieskovská, B. Bučko, K. Zábovská, Comparison of CNN-based models for pothole detection in real-world adverse conditions: Overview and evaluation, Appl. Sci. 13 (9) (2023) http://dx.doi.org/10.3390/app13095810.

[6] H. Liu, H. Wang, Real-time anomaly detection of network traffic based on CNN, Symmetry 15 (6) (2023) http://dx.doi.org/10.3390/sym15061205.

[7] T. Zhao, Y. Wei, A road surface image dataset with detailed annotations, 2022, http://dx.doi.org/10.17632/w86hvkrzc5.2, Mendeley Data, V2.

[8] H. Lee, K. Hwang, M. Kang, J. Song, Black ice detection using CNN for the prevention of accidents in automated vehicle, in: 2020 International Conference on Computational Science and Computational Intelligence, CSCI, 2020, pp. 1189–1192, http://dx.doi.org/10.1109/CSCI51800.2020.0022.

[9] Y.E. Abdalla, M.T. Iqbal, M. Shehata, Black ice detection system using kinect, in: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering, CCECE, 2017, pp. 1–4, http://dx.doi.org/10.1109/CCECE.2017.7946722.

[10] M. Najafi, S. Gorgin, M.K. Fallah, G. Jaberipur, J.-A. Lee, Low-power BLACK-ICE detection for safety critical edge devices on roads, in: 2024 Fifteenth International Conference on Ubiquitous and Future Networks, ICUFN, 2024, pp. 636–641, http://dx.doi.org/10.1109/ICUFN61752.2024.10625231.

[11] J. Kim, E. Kim, D. Kim, A black ice detection method based on 1-dimensional CNN using mmwave sensor backscattering, Remote. Sens. 14 (20) (2022) http://dx.doi.org/10.3390/rs14205252.

[12] C. Bhattacharyya, S. Kim, Black ice classification with hyperspectral imaging and deep learning, Appl. Sci. 13 (21) (2023) http://dx.doi.org/10.3390/app132111977.

[13] R. Sharma, A. Kamra, A review on CLAHE based enhancement techniques, IC3I, in: 2023 6th International Conference on Contemporary Computing and Informatics, vol. 6, 2023, pp. 321–325, http://dx.doi.org/10.1109/IC3I59117.2023.10397722.

[14] T. Saini, R. Gandhi, S. Roy, M. Diwakar, P. Singh, A.K. Mishra, Person re-identification using deep learning, in: 2024 4th International Conference on Advancement in Electronics & Communication Engineering, AECE, 2024, pp. 509–512, http://dx.doi.org/10.1109/AECE62803.2024.10911558.

[15] M. Sandler, A.G. Howard, M. Zhu, A. Zhmoginov, L. Chen, Mobilenetv2: Inverted residuals and linear bottlenecks, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 4510–4520, http://dx.doi.org/10.48550/arXiv.1801.04381.

[16] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[17] A.S.M. Thabit, C.A. Kerrache, C.T. Calafate, A survey on monitoring and management techniques for road traffic congestion in vehicular networks, ICT Express 10 (6) (2024) 1186–1198, http://dx.doi.org/10.1016/j.icte.2024.10.007.

[18] M. Golam, A. Md Tayeb, M. Ayesha Khatun, M. Facklasur Rahaman, A. Aouto, O. Paul Angelo, D.-S. Kim, J.-M. Lee, J.-H. Kim, BlackIceNet: Explainable AI-enhanced multimodal for black ice detection to prevent accidents in intelligent vehicles, IEEE Internet Things J. 12 (11) (2025) 15558–15571, http://dx.doi.org/10.1109/JIOT.2025.3530565.

[19] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S.E. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, A. Rabinovich, Going deeper with convolutions, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9, http://dx.doi.org/10.48550/arXiv.1409.4842.

[20] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, 2014, http://dx.doi.org/10.48550/arXiv.1409.1556, ArXiv Preprint, arXiv:1409.1556.

[21] J. Redmon, A. Farhadi, YOLO9000: better, faster, stronger, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 7263–7271, http://dx.doi.org/10.48550/arXiv.1612.08242.

[22] T. Wang, T. Lin, Z. Liu, X. Xie, S. Yao, ADPGAN: Adaptive differential privacy-preserving GAN for image privacy, Inf. Fusion 125 (2026) 103515, http://dx.doi.org/10.1016/j.inffus.2025.103515, URL https://www.sciencedirect.com/science/article/pii/S1566253525005871.