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Black Ice Detection Platform and Its Evaluation using Jetson Nano Devices based on Convolutional Neural Network (CNN)

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Abstract

In this paper, we propose a black ice detection platform framework using Convolutional Neural Networks (CNNs). To overcome black ice problem, we introduce a real-time based early warning platform using CNN-based architecture, and furthermore, in order to enhance the accuracy of black ice detection, we apply a multi-scale dilation convolution feature fusion (MsDC-FF) technique. Then, we establish a specialized experimental platform by using a comprehensive dataset of thermal road black ice images for a training and evaluation purpose. Experimental results of a real-time black ice detection platform show the better performance of our proposed network model compared to conventional image segmentation models. Our proposed platform have achieved real-time segmentation of road black ice areas by deploying a road black ice area segmentation network on the edge device Jetson Nano devices. This approach in parallel using multi-scale dilated convolutions with different dilation rates had faster segmentation speeds due to its smaller model parameters. The proposed MsCD-FF Net(2) model had the fastest segmentation speed at 5.53 frame per second (FPS). Thereby encouraging safe driving for motorists and providing decision support for road surface management in the road traffic monitoring department.

Keywords : Black ice detection, Convolutional Neural Network (CNN), Multi-scale dilation convolution, Feature fusion, Road safety

Major Classification Code: Artificial Intelligence, etc

1. Introduction

Black ice, a thin layer of ice that forms on road surfaces, can significantly reduce road friction. It typically develops when temperatures drop below freezing, causing moisture on the road to freeze. This transparent hazard is hard to spot and is often mistaken for wet or snowy roads, making it especially treacherous for both pedestrians and drivers. Black ice tends to occur in shaded areas like mountainous regions, tree-lined roads, tunnel entrances, and bridges where sunlight can't reach. This phenomenon poses a substantial risk to motorists, leading to a higher likelihood of accidents, injuries, and even fatalities (Park et al., 2017, Smith et al., 2017). According to the Federal Highway Administration, more than 116,800 people are injured in vehicle accidents caused by snowy, slushy, or icy roads annually in the USA.

Moreover, accidents caused by black ice can lead to secondary and tertiary damages, resulting in major disasters and an increased risk of chain collisions. While recent advancements in road condition detection-based early warning systems for traffic safety have gained attention,

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comprehensive research on black ice detection remains limited.

In recent years, there has been a proliferation of effective image classification networks, driven by advancements in deep learning technology. However, most road surveillance cameras utilize conventional cameras that capture visible light in the RGB spectrum, which spans from 0.43μm to 0.79μm. In environments with insufficient lighting, the quality of these images can easily degrade. In contrast, thermal cameras rely on the principle of capturing thermal radiation emitted by all objects with temperatures higher than absolute zero. They operate around the clock and are impervious to adverse weather conditions such as clouds and fog. Additionally, thermal cameras exhibit high sensitivity and extended detection ranges, making them indispensable in target recognition and detection applications. They find widespread use in security monitoring, remote sensing, defense, and various other fields.

Therefore, this paper conducts research on the process of black ice formation, creates a simulation environment for black ice formation, collects thermal road black ice images using thermal cameras, and establishes a dataset of thermal road black ice. In this paper, the cloud-edge collaborative architecture of early black ice detection and warning system is proposed. This platform is designed to enhance the accuracy of road black ice extraction by applying a convolutional neural network-based black ice segmentation network model and adopt the image detection enhancement technique such ad a multi-scale dilation convolution feature fusion (MsDC-FF) technique, enhancing the CNN's ability to identify black ice regions effectively. Furthermore, this detection and warning system is designed to deploy it on a high-performance cloud data processing center.

Section 2 provides an overview of related work on black ice detection and Section 3 presents the methodology and architectural details of the proposed real-time warning system in detail. In Section 4, we will discuss the experimental setup and results, including the construction of our thermal road black ice dataset. The concluding remark is presented in the last section.

2. Related Work

Many studies have explored black ice detection using image-based methods, Q. Lin et al. (2017) designed a road icing detection system based on OpenCV+Python, and a Support Vector Machine (SVM) classifier was employed to identify four types of road conditions: dry, wet, snowy, and icy. Habib Tabatabai et al. (2017) conducted a study to detect black ice, ice and water in roads and bridges using sensors embedded in concrete. Youngis E. Abdalla et al (2017) and Xinxu Ma et al. (2020) proposed systems for detecting black ice using different technologies. Youngis E. Abdalla et al. (2017) used Kinect to classify ice types and measure thickness, showing effective black ice detection. Xinxu Ma et al. (2020) employed three wavelengths of non-contact optical technology to distinguish ice conditions and successfully identified black ice through reflectance. Both studies suggest effective methods for black ice detection. Hojun Lee et al. (2020) created a black ice detection dataset using Google image search and utilized CNN deep learning techniques to detect dry, wet, snowy, and black ice conditions, achieving a recognition rate of 96%. These research works highlight the effectiveness of using CNN-based methods for black ice detection.

With the widespread availability of cameras, images have become a convenient, fast, and cost-effective method for acquiring road information. Previous research on image detection has generally adopted neural network models such as FCN, U-Net, DeepLabv3+, PSPNet, ENet, and LinkNet.

FCN: Long, Shelhamer & Darrel (2015) introduced a Fully Convolutional Network with imprecise edge segmentation due to information loss during down-sampling and up-sampling.

U-Net: Ronneberger et al. (2015) proposed an encoder-decoder model with concatenation of feature maps for improved segmentation.

DeepLabv3+: Chen et al. (2017) revisited DeepLabv3+ with dilated convolutions, ASPP, and CRF post-processing for accurate segmentation.

PSPNet: Zhao et al. (2017) combined ResNet and dilated networks with parallel pooling and up-sampling for scale-specific feature information and refined segmentation.

ENet: Paszke et al. (2016) introduced an efficient neural network with bottleneck modules and filter decomposition for precise segmentation and reduced complexity.

LinkNet: Chaurasia & Culurciello (2017) proposed a network with residual modules for enhanced feature extraction and optimized computation in real-time segmentation.

3. Methodology

3.1. Platform Architecture of Real-Time Warning System Black Ice Detection

Typically, images captured by cameras installed on roads are sent directly to cloud data centers for processing and recognition. However, transmitting all images to the cloud data center can lead to increased end-to-end latency and higher bandwidth consumption, causing data transmission to become a bottleneck in data processing. Since the actual collected images often include a significant amount of redundant frames, such as road footage without black ice, sending this meaningless data to the cloud data center results in not only wasted storage but also more severe end-to-end latency and bandwidth consumption.

Furthermore, sending images to a remote cloud data center for processing and recognition in road traffic monitoring does not meet the real-time requirements of traffic information. To address these issues, this paper proposes a cloud-edge collaborative warning system for real-time road black ice, combining edge computing technology and deep learning, as illustrated in Figure 1.

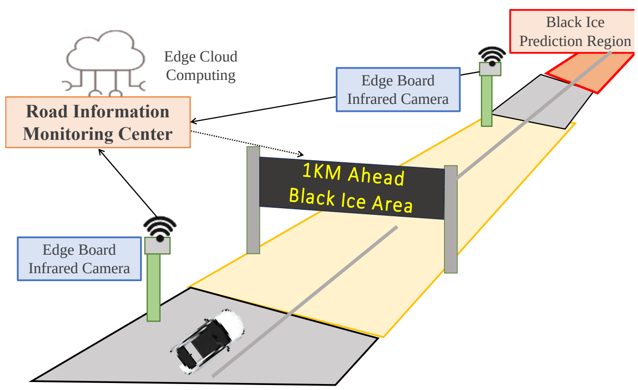


Figure 1: Illustration of a cloud- edge collaborative wanring system of real-time road black ice

As shown in Figure 1, edge computing technology provides a certain level of computational capability to road surveillance cameras. By adding edge computing modules near surveillance cameras and deploying the inference portion of a small deep learning network on the edge computing module, collected image data can be processed and recognized directly, significantly reducing the computational burden on cloud data processing centers. This, in turn, reduces system-wide latency and power consumption, enabling real-time road black ice alerts.

The proposed cloud-edge collaborative architecture of Figure 1 is designed to enhance the accuracy of road black ice extraction by training a deep convolutional neural network-based black ice segmentation network model and deploying it on a high-performance cloud data processing center. Additionally, the trained deep learning model is deployed on edge devices to meet the real-time requirements for black ice area detection.

3.2. System Model of Real-Time Warning System Black Ice Detection

The proposed real-time road black ice "cloud-edge" collaborative warning system consists of three layers: the thermal imaging data collection layer, the edge computing layer, and the cloud data processing center, which serves as the road traffic monitoring center. This configuration is depicted in Figure 2.

Infrared Camera IoT Layer: The TPV-IAHDR thermal camera is used to collect road images.

Edge Computing Layer: The edge computing layer is primarily responsible for inference regarding road black ice. In this paper, the NVIDIA Jetson Nano edge development board is utilized to download and deploy the black ice segmentation model trained in the cloud. It performs real-time analysis of road images collected by the thermal camera, segmenting the black ice areas. When black ice areas are detected in the collected images, it classifies the severity grade based on the segmented black ice size, displays warnings on LED display boards in real-time, sends text messages to the road monitoring center, and saves black ice area road images collected every 10 seconds while periodically uploading them to the cloud.

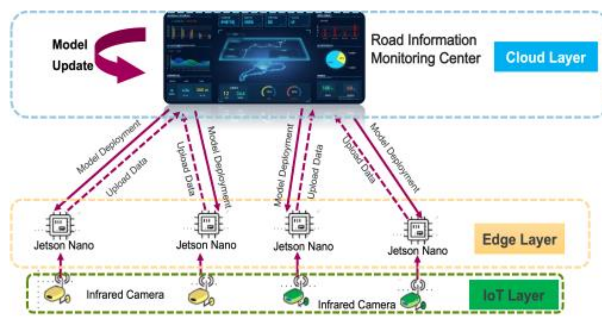


Figure 2: System Model of Cloud-edge Warning Collaborative System

Cloud Data Processing Center Layer: In this paper, a cloud data processing center is simulated using an Ubuntu server. The deep learning network is trained using the constructed thermal road black ice dataset to create a deep convolution-based thermal road black ice area segmentation network model. This trained model is deployed on the edge computing nodes. It intercepts real-time warning messages received from the edge layer, makes road management decisions, and periodically downloads the stored thermal road black ice images from the edge nodes to execute the road black ice area segmentation network model

3.3. Workflow of the Cloud-edge Warning Collaborative System

The approach presented in this paper includes both an offline module for training the black ice area segmentation network and an online module for real-time black ice area segmentation.

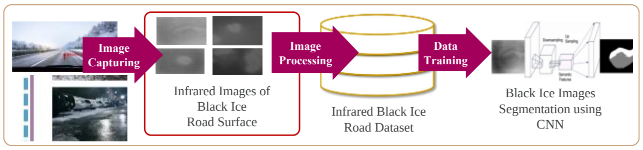


Figure 3: Illustration of black ice semantic segmentation training module (offline module)

As shown in Figure 3, the offline module involves creating a simulated road black ice generation process to construct a road black ice experimental environment. This simulation is carried out to generate road black ice using the TPV-IAHDR thermal camera, collecting black ice images from both cement and asphalt road materials. Subsequently, a black ice dataset is created using the collected images. Using this constructed black ice dataset, a deep convolution-based black ice semantic segmentation network model is trained on a high-performance server in the simulation cloud processing center. Finally, the trained black ice semantic segmentation network model is deployed on the Jetson Nano edge development board. The flowchart of the real-time road black ice area warning module is depicted in Figure 4.

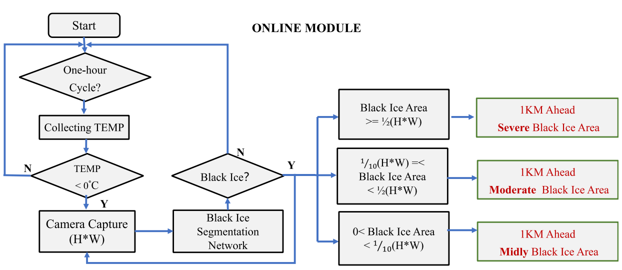


Figure 4: Workflow of Real-time Black Ice Region Warning Module

In the real-time black ice area warning module, the road surface temperature falling below 0℃ serves as the trigger signal for the entire system. When the road surface temperature is measured to be below 0℃, the system initiates road surface image collection and subsequent processing. Temperature measurement is obtained through temperature sensors, and if the temperature is determined to be above 0℃, the system enters a dormant state for one hour before rechecking the temperature. If the road surface temperature is below 0℃, the thermal camera is activated, and road surface images are collected. The images are processed using the black ice semantic segmentation network model trained in the offline module to recognize black ice areas within the images.

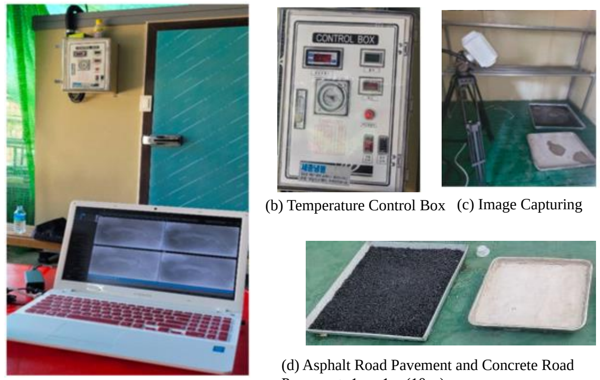
If no black ice areas are detected in the recognized images, the system enters a dormant state for one hour before performing another temperature check. However, if black ice areas are identified in the collected images, they are classified based on the size of the segmented black ice areas. When the size of the black ice area is greater than half of the collected image, the road LED warning display board shows "1km ahead, severe black ice area." If the black ice area size falls within [1/10, 1/2] of the collected image size, the board displays "1km ahead, moderate black ice area." For black ice areas with a size in the range of [1/20, 1/10] of the collected image, the board displays "1km ahead, light black ice area."

This real-time black ice warning system dynamically sends black ice severity alerts to drivers, enabling them to preemptively brake and reduce driving speed for safer travel. Simultaneously, the traffic monitoring center swiftly assesses the road black ice situation in response to alerts, takes measures to address the black ice, ensuring safe travel, and reducing the occurrence of traffic accidents, which benefits road management as well.

3.4. CNN Network for Black Ice Image Segmentation

This paper introduces a CNN-based architecture for real-time black ice detection with an encoder-decoder network for infrared images. Based on constructed infrared black ice road data set, our CNN-based model is trained for establishing a comprehensive dataset of thermal road black ice images for a training and evaluation purpose. The block diagram of the CNN based network architecture is shown in Figure 5, which illustrates encoder and decoder block diagram of the parallel execution of convolution with Multi-Scale Dilated Convolutional Feature Fusion (MsDC-FF) module (Kang, S. 2023).

The network architecture adopted in this paper has been proposed by Kang (2023), which is divided into two parts: an encoder and a decoder. The encoder consists of three stages of encoder blocks, while the decoder consists of four stages of decoder blocks, as shown in Figure 5. To reduce the model size, the early stages of the encoder block use two convolution layers to reduce the resolution to one-fourth and restore the original image size through convolution layers after passing through the decoder. Figure 5 shows the encoder block with multi-scale dilated convolutional feature fusion (MsDC-FF) module with scalable dilation ratio.



(a) Image Saving (b) Temperature Control Box (c) Image Capturing (d) Asphalt Road Pavement and Concrete Road Pavement; 1m x1m (10ea)

Figure 5: Experimental setup picture of Taking Images of Infrared Road Black Ice Experiment; (a) Image Saving, (b) Temperature Control Box, (c) Image Capturing, (d) Samples of Asphalt Road and Concrete Road Pavement.

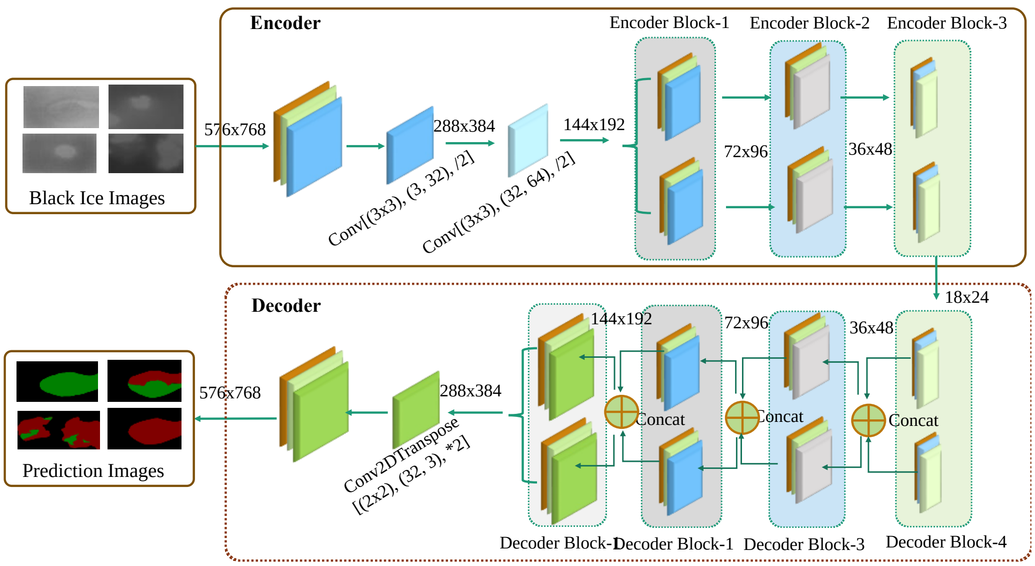


Figure 6: Encoder and Decoder Block Diagram of the Paralled Execution of Convoultion with Multi-Scale Dilated Convolutional Feature Fusion (MsDC-FF) Module (Kang, S. 2023).

4. Simulation and Results

4.1. Experimental Setup

The experimental study of road black ice formation involved creating a simulation experimental environme nt for road black ice generation, ultimately building a thermal road black ice dataset. The simulation experim ental environment is depicted in Figure 6.

To obtain various black ice images, this paper followed the process outlined in Figure 6. Ten 1-meter square asphalt and cement roads, each with a thickness of 5cm, were created. These roads were installed in a freezing facility, and water was sprayed on them. Subsequently, thermal cameras were used to capture images of the black ice formation. Different cases were created by varying the area and location of water application, resulting in a total of 10 different scenarios.

4.2. Image Dataset

The simulation setup used in this paper is as followings: TPV-IAHDR thermal cameras were used to capture the entire process of black ice formation from the beginning in a video with a resolution of 1280x720. Figure 7 illustrates an example of the gradual formation of black ice, starting from a wet road surface, in one specific case.

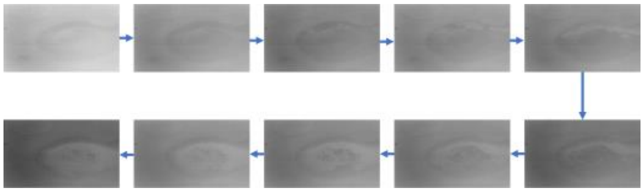


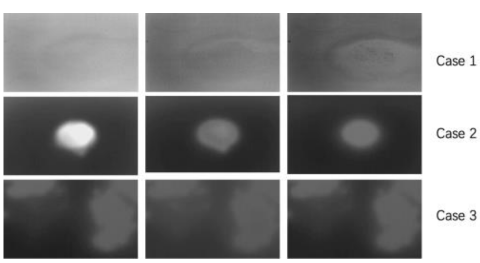
Figure 7: An example of the gradual formation of black ice on a wet road surface.

These thermal camera images are used for training image dataset, by sampling and cropping frames at intervals of 200ms. This established total 1,156 black ice road images for 10 different cases and then, these images were divided into training, validation, and test datasets according to a ratio of 6:2:2. Therefore, the thermal road black ice dataset constructed in this paper is as shown in Table 1. The image dataset of the thermal road black ice was generated on asphalt roads and cement roads for different cases.

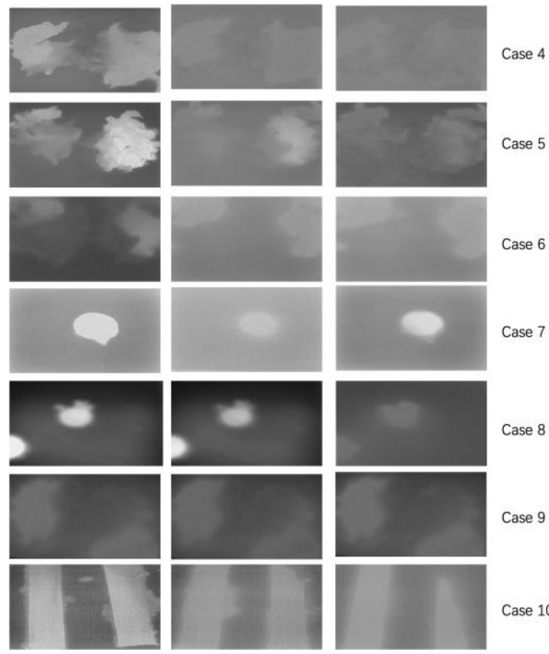
Table 1: Number of infrared black ice road furface images

Dataset Type	No. of Images
Train Dataset	697
Validation Dataset	229
Test Dataset	229
Total Dataset	1156

The examples of the thermal road black ice image dataset constructed in this paper are shown in Figure 8. Figure 8(a) displays three example images of black ice generated on asphalt roads, and Figure 8(b) shows seven example images of black ice generated on cement roads.



a) Asphalt Cases



b) Cement Cases

Figure 8: Examples of Infrared Road Black Ice Image in Different Cases

These images are labeled by open-source image annotation tool, Labelme as shown in Figure 9. This displays some of the original images used in the paper along with their corresponding mask images.

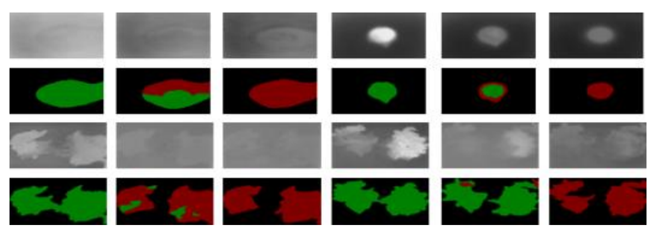


Figure 9: Example of original images and labeled or masked images of black ice generated on asphalt roads and cement roads for different cases

4.3. Experiments and Results on Jetson Nano

The experimental setup was conducted on the following platform: to use Ubuntu 18.04 LTS as OS, to use GPU of four NVIDIA GeForce RTX 2080 Ti with 11GB of memory each. The deep learning frameworks used were Keras and TensorFlow. In the simulation, the number of epochs was set to 100, and batch sizes of 1, 2, 4, 8, and 16 were tested. During the training process, the cross-entropy loss function was utilized, and the Adam optimizer was employed with a learning rate of 0.001. Learning rate decay was applied to expedite the learning process.

The performance comparison metric of the accuracy of black ice area detection used in this paper is mIoU (Mean Intersection over Union) metric. Meanwhile IoU is a measure of the overlap between the segmentation result and the ground truth, mIoU is the ratio of the intersection and union of quantized results and ground truth values as in Eq. (1).

$$m\text{IoU} = \frac{1}{N} \sum_{i=1}^{N} \frac{\mathrm{X}_{ii}}{T_i + \sum_{j=1}^{N}(\mathrm{X}_{ji} - \mathrm{X}_{ii})} \quad (1)$$

where N represents the number of pixel classes in the image, Ti denotes the total number of pixels for class i, X_{ii} represents the number of pixels where the true class is i and the predicted class is also i, and X_{ji} represents the number of pixels where the true class is i but the predicted class is j. *m*IoU is a simple and representative metric widely used to evaluate the segmentation results of networks in most image segmentation tasks.

The results of real-time thermal imaging road black ice area segmentation on Jetson Nano are as shown in Table 2, where FPS (frames per second) represents the total number of video segments that can be processed per second.

Table 2: Experimental Results on Jetson Nano

Network Model	FPS	*m*IoU(%)		Black Ice IoU(%)	
		8	16	8	16
U-Net	0.24	69.69	-	61.38	-
PSPnet	0.14	85.85	-	83.27	-
DeepLabV3+	0.19	93.65	-	88.20	-
ENet	1.95	94.35	94.36	93.81	93.10
LinkNet	3.72	95.39	**95.48**	**94.37**	94.33
MsCD-FF Net(P2)	5.53	95.93	95.61	94.87	94.48
MsCD-FF Net(P3)	5.26	96.16	96.02	95.18	94.94
MsCD-FF Net(P4)	4.98	96.35	96.07	95.32	94.97
MsCD-FF Net(P5)	4.64	96.39	95.90	95.41	94.75
MsCD-FF Net(P6)	4.35	96.40	96.31	95.34	95.25
MsCD-FF Net(P7)	4.10	96.43	96.33	95.43	95.29
MsCD-FF Net(P8)	3.84	96.44	96.31	95.48	95.25
MsCD-FF Net(P9)	3.63	**96.46**	96.37	**95.46**	95.34

As can be seen in Table 2, the segmentation speeds of each network model vary significantly. Among them, U-Net, PSPNet, and DeepLabV3+ have slower segmentation speeds due to their large model size and computational demands, with all of them achieving FPS values of 1 or lower, indicating that they cannot satisfy real-time black ice area segmentation. On the other hand, ENet and LinkNet achieve FPS values of 1.95 and 3.72, respectively, which means they can perform real-time black ice area segmentation.

As shown in Figure 10, the 5 networks highlighted in green color of the conventional networks, while the 8 networks highlighted in orange color represent the MsCD-FF Net(P*i*) network adopted and proposed by Kang (2023). Overall, the network that fuses features in parallel using multi-scale dilated convolutions with different dilation rates according to the proposed resolution in this paper had faster segmentation speeds due to its smaller model parameters. Except for MsCD-FF Net(9), which had an FPS of 3.63, slightly lower than LinkNet, the rest of the models had higher FPS values compared to LinkNet. Among these, MsCD-FF Net(2) had the fastest segmentation speed at 5.53 FPS, while the other networks had slower segmentation speeds and lower FPS values as the number of parallel dilated convolutions increased, resulting in higher computational requirements.

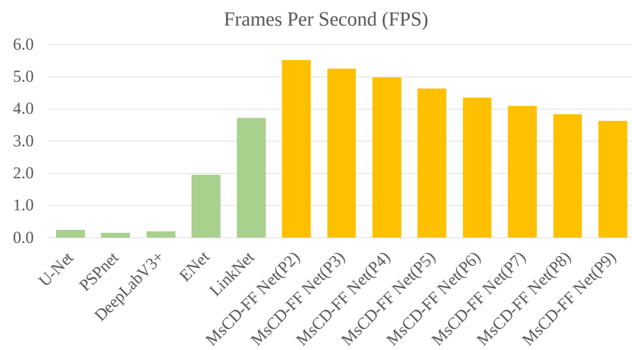


Figure 10: FPS comparisons of neural networks when using Jetson nano devices

The screen for real-time thermal imaging road black ice area segmentation on Jetson Nano is shown in Figure 11. In the top-left corner of Figure 10, the black ice segmentation FPS of the network is displayed, and in real-time, black ice severity level alerts are also presented based on the results of the black ice segmentation.

Figure 11: Black Ice Level Warning in Real-time on Jetson Nano

5. Conclusion

The proposed a black ice detection platform framework using CNNs presents a real-time based early warning platform using CNN-based architecture. Furthermore, in order to enhance the accuracy of black ice detection, MsDC-FF with a specialized experimental platform using a comprehensive dataset of thermal road black ice images are setup for an experimental simulation. The proposed platform has achieved real-time segmentation of road black ice areas by deploying a road black ice area segmentation network on the edge device Jetson Nano devices. It is shown that the proposed model using MsCD-FF with different dilation rates had faster segmentation speeds due to its smaller model parameters. Except for MsCD-FF Net(9), which had an FPS of 3.63, slightly lower than LinkNet, the rest of the models had higher FPS values compared to LinkNet. Among these MsCD-FF Net(2) model had the fastest segmentation speed at 5.53 FPS.

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