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Global-Similarity Local-Salience Network for Traffic Weather Recognition

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ABSTRACT Recognizing the current weather conditions from a single image is of great theoretical significance. It also has potential practical value for daily life and traffic scheduling. To achieve that, typical weather recognition methods focus on learning a general weather description, e.g., sunny, cloudy, foggy, rainy and snowy etc, for the overall weather condition. However, it is far away from being sufficient for many tasks especially traffic management and control. To solve this key problem, this paper proposes a Global-Similarity Local-Salience Network (abbreviated as GSLSNet) for traffic weather recognition. Specifically, a simple but effective Global-Similarity Module (GSM) is proposed to recognize the overall weather condition and a Local-Salience Module (LSM) is presented to restrict the network to focus on road weather details. Besides, this paper also provides a new traffic weather dataset, named TWData, which is the first fine categorized dataset especially for highway weather recognition. Experimental results compared with state-of-the-art methods on both public datasets and TWData demonstrate the superiority of the proposed GSLSNet.

INDEX TERMS Weather recognition, global similarity, local salience, traffic image.

I. INTRODUCTION

Weather recognition plays a fundamental role in daily applications, such as traffic management [1], street analysis [2], self-driver assistance [3]–[5] and robot navigation [6]. It is also of great significance for both computer vision and pattern recognition tasks [7]–[13].

Traditional weather recognition methods relies largely on the meteorological stations with expensive sensors and human observations. However, the recognized weathers are largely restricted by these sensors [14]. Recently, with the wide spread of web and mobile cameras, people prefer to obtain an accurate weather description from images. Recognizing the weather conditions from traffic cameras timely can also provide accurate traffic scheduling for transport agency.

Under the basic framework of discriminative feature extraction and effective pattern classification, a possible solution for weather recognition is treating it as image classification, from the perspective of machine learning. Casting on this assumption, many research focused on extracting powerful features such as region histogram [15], region template [16], global histogram [17], Sobel edge [18] and power spectrum [4], [5] etc for weather description. There are also methods devoted to seeking more effective classification models such as Support Vector Machine (SVM) [7], k-Nearest Neighbor (KNN) [14] and Convolutional Neural Networks (CNN) [10], [19]–[23].

As a part of daily life, the traffic condition is easily affected by current weathers. Typical weather recognition methods tend to divide them into simple categories such as sunny, cloudy, foggy, rainy, snowy or combinations of them, which is inadequate for traffic management and control. Basically, people focus more on detailed road conditions such as "the road is covered with snow", "the road is wet", or "the road is icing", instead of simple descriptions "it is snowy" or "it is rainy". To resolve these issues, this paper provides a new model and a new dataset for traffic weather recognition. The contributions of this paper are summarized as follows.

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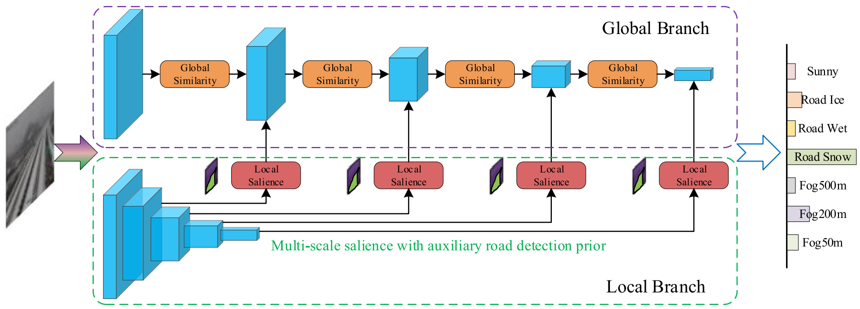

FIGURE 1. An illustration of the proposed Global-Similarity Local-Salience Network. GSLSNet contains two branches, i.e., the Global Branch and the Local Branch, corresponding to the Global Similarity Module and the Local Salience Module, respectively.

1) Benefitting from both channel-wise and spatial-wise attention, a global similarity module (GSM) is proposed to capture the general weather condition.
2) A local salience module (LSM) with road prior is introduced, for the purpose of restricting the model to focus on road weather details.
3) Casting on GSM and LSM, a global-similarity local-salience network (GSLSNet) is presented for traffic weather recognition from single images.
4) A new traffic weather dataset (TWData) with accurate weather labels is provided. To the best of our knowledge, it is the first weather classification dataset especially collected for traffic weather recognition.

II. RELATED WORKS AND MOTIVATION

This paper aims to recognize the current road weather details given a single traffic image. Recognizing the outdoor weather condition is important to daily travel [24], [25] and industrial scheduling [26], [27]. Early weather classification methods simply assign the given image as either sunny or cloudy [7], [11], while some research enriches the labels into overcast [28], rainy, foggy [15] and haze [17].

One key ingredient of accurate weather recognition is how to extract the discriminative features. To achieve this, many handcrafted features are elaborately designed. Yan *et al.* [17] combines multiple elements including histogram of gradient amplitude, HSV color histogram and road information as the feature and employs AdaBoost for weather classification. Roser and Moosmann [15] proposes a new weather descriptor that can distinguish heavy rain and fog by taking the visibility affects into consideration. Considering the accessible daily weather condition, Lu *et al.* [7], [11] applies the corresponding daily weather cues as an additional complementation. The contrast, saturation, edge gradient and power spectral slop [29] are also proved to be effective to recognize the weather conditions. With the overwhelming successes of deep learning among computer vision tasks, many CNN models have been designed recently. Specifically, Elhoseiny *et al.* [10] first proposes to employ AlexNet, An *et al.* [20] employs ResNet for single image weather recognition. Guerra *et al.* [30] exploits multiple architectures and demonstrates the superiority of CNN feature to handcrafted features. Basically, several weather conditions tend to occur simultaneously, e.g., foggy and cloudy, therefore, Zhao *et al.* [22], [23] extends weather recognition from single-label classification to multi-label learning. To reduce parameter redundancy, Liu *et al.* [2] takes the advantage of sparse decomposition and cuts down the CNN computation dramatically. There are also methods employing multiple kernel learning and active learning for weather recognition.

To our motivation. Early research has demonstrated the feasibility of classifying weathers into sunny, cloudy, snowy, rainy or foggy from outdoor or vehicle images. However, to provide more accurate traffic scheduling, recognizing the road weather details is more imperative. This mechanism motivates us to build a model that can not only identify the general weather condition (e.g., sunny, rainy, foggy) but also distinguish the road weather details (e.g., the road is wet, the road is covered with snow).

III. GLOBAL-SIMILARITY LOCAL-SALIENCE NETWORK

To obtain an accurate weather description for traffic images, this paper proposes a Global-Similarity Local-Salience Network (GSLSNet). An intuitive illustration of GSLSNet can be found in Figure 1. Basically, GSLSNet comprises two modules, i.e., Global Similarity Module (GSM) and Local Salience Module (LSM), to obtain a general weather description accompanied by an accurate road weather detail.

A. GLOBAL SIMILARITY MODULE

Global Similarity Module (GSM) is designed to recognize the overall weather conditions of given images. The motivation behind this design is that the weathers within a single image tend to be consistent. To achieve that, both a channel-wise branch and a spatial-wise branch are employed (see Figure. 2 for details).

Specifically, suppose the input feature is denoted as $\mathcal{F} \in \mathbb{R}^{W \times H \times C}$, channel-wise branch first obtains a global description $\mathcal{G}'_C \in \mathbb{R}^{1 \times 1 \times C}$ among channels via Global Average Pooling (GAP). One-dimension convolution (Conv1d) is employed to transform this descriptor into a latent space, and

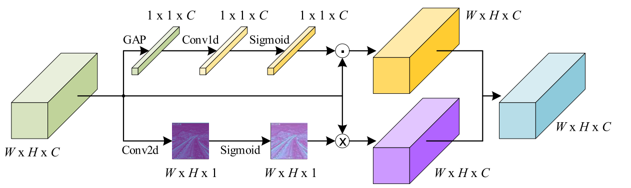

FIGURE 2. An illustration of the proposed Global-Similarity Module.

the transformed descriptor $\mathcal{G}_C'' \in \mathbb{R}^{1\times 1\times C}$ is denoted as

$$\mathcal{G}_C'' = \mathrm{Conv1d}(\mathcal{G}_C'). \tag{1}$$

To distinguish the importance of different channels, the Sigmoid activation is utilized and the final output $\mathcal{G}_C \in \mathbb{R}^{W\times H\times C}$ of the channel-wise branch can be denoted as

$$\begin{aligned}\mathcal{G}_C &= \mathcal{F} \odot \mathrm{Sigmoid}(\mathcal{G}_C'') \\ &= \mathcal{F} \odot \mathrm{Sigmoid}(\mathrm{Conv1d}(\mathcal{G}_C')) \\ &= \mathcal{F} \odot \mathrm{Sigmoid}(\mathrm{Conv1d}(\mathrm{GAP}(\mathcal{F}))),\end{aligned} \tag{2}$$

where $\odot$ represents vector-tensor multiplication.

Basically, channel-wise branch can obtain a global description of given feature maps while ignore spatial correlation. To take these information into consideration, a simple spatial-wise branch is employed. Similarly, the input feature $\mathcal{F} \in \mathbb{R}^{W\times H\times C}$ is first transformed to a latent space via two-dimension convolution (Conv2d). After that, a spatial-aware description $\mathcal{G}_S \in \mathbb{R}^{W\times H\times C}$ is obtained via

$$\mathcal{G}_S = \mathcal{F} \otimes \mathrm{Sigmoid}(\mathrm{Conv2d}(\mathcal{F})) \tag{3}$$

where $\otimes$ represents matrix-tensor multiplication.

Finally, the output $\mathcal{G} \in \mathbb{R}^{W\times H\times C}$ of GSM is defined as $\mathcal{G} = \mathcal{G}_C + \mathcal{G}_S$, and $\mathcal{G}$ comprises the global information of both channel-wise and spatial-wise accordingly. Benefitting from both of these two branches, GSM is capable of obtaining a general descriptor of integral weather condition.

B. LOCAL SALIENCE MODULE

Nevertheless, the road weather details many vary from its corresponding surroundings in some cases. For example, the road surroundings may covered with snow while the road itself not due to manual cleanup, and the road surroundings might be wet while the road is dry due to different heat capacities. Consequently, a Local Salience Module (LSM), which can distinguish the road weather details is imperative. Basically, the commonly used lane detection techniques, such as ENet [31], SegNet [32] or DeepLab [33] can be exploited.

However, the purpose of LSM is to exploit the road weather details instead of the road itself. Inspired by the principle of ENet [31], each LSM block (LSB) comprises four convolutional layers with different strides.

Formally, suppose the input of LSB is denoted as $\mathcal{F} \in \mathbb{R}^{W\times H\times C}$, the corresponding output can be represented as

$$\mathcal{L}_E' = \underbrace{\mathrm{ReLU}(\mathrm{Conv2d}}_{\times 3}(\mathrm{ReLU}(\mathrm{Conv2d}(\mathcal{F}, s=2)), s=1)). \tag{4}$$

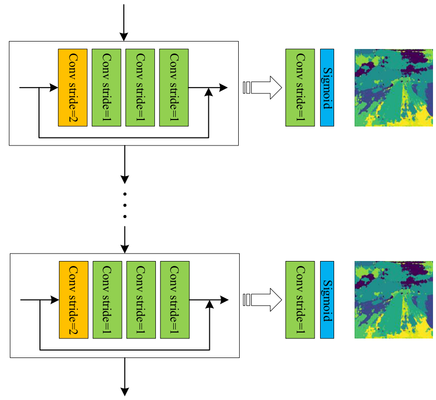

FIGURE 3. An illustration of the proposed Local-Salience Module.

In experiments, the LSBs are pre-trained on road detection tasks and the outputs of LSBs are capable of highlighting the road information (see Figure. 7 for details). In order to restrict the weather recognition network to focus on road weather details, one additional convolutional layer with sigmoid activation is implemented, i.e.,

$$\mathcal{L}_E = \mathrm{Sigmoid}(\mathrm{Conv2d}(\mathcal{L}_E')). \tag{5}$$

The final output of LSM is represented as

$$\mathcal{O} = \mathcal{G}_S \otimes \mathcal{L}_E. \tag{6}$$

Typically, the guiding information from multiple layers is necessary. A more detailed illustration about LSM can be found in Figure. 3. Also note that the key point of LSM is not a new road detection block but to pour road priors to weather recognition networks, which can promote the network to focus on road weather details and improves the weather recognition accuracy.

C. GSLSNet

GSM and LSM can be added to any state-of-the-art networks, e.g., MobileNet [37], ShuffleNet [38], VGG [39] and ResNet [40], resulting to the proposed GSLSNet. A detailed comparison can be found in section V. And an intuitive illustration of GSLSNet can be found in Figure. 1.

Also note that GSLSNet is mainly inspired by the prevalent attention mechanism, e.g., Soft Attention Mechanism [41], Weak Sematic Attention [42] and Efficient Channel Attention (ECA) [43]. However, GSLSNet differs from these attention frameworks in many aspects and has the following advantages.

1) The GSM has two branches, i.e., channel-wise branch and spatial-wise branch, while other attention methods, e.g., Efficient Channel Attention [43] or Weak Semantic Attention [42], contains only a single channel- or spatial-wise branch. Benefiting from both of the two branches, GSM is capable of fetching not only more detailed spatial-relevance but also channel-dependent information.

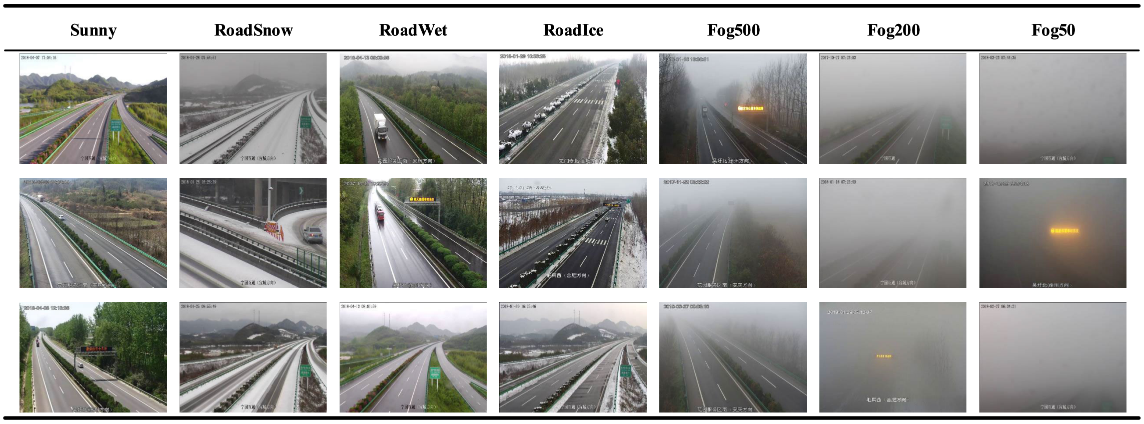

FIGURE 4. Examples of TWData. TWData contains seven detailed categories, i.e., *Sunny*, *Fog50*, *Fog200*, *Fog500*, *RoadSnow*, *RoadWet* and *RoadIce*.

2) As illustrated in section I, the purpose of GSLSNet is to recognize the road weather details. The road priors are dexterously represented by a road detection network, which promotes the network for road weather recognition. Experimental results on Table. 3 and Figure. 7 also demonstrate the superiority of this mechanism.
3) GSLSNet is the first weather recognition network that especially designed for highways. Different from typical object recognition or outdoor weather recognition networks, GSLSNet is more specific that can be implemented to traffic management.

IV. TRAFFIC WEATHER DATASET

Basically, the traffic management agency pays more attention to road weather details, e.g., "the road is icing" or "the visibility of current road is lower than 50m", instead of a general and simple description "sunny" or "foggy". To illustrate this key issue and to demonstrate the effectiveness of the proposed GSLSNet for traffic weather recognition, this paper provides a new dataset named TWData (abbreviation of Traffic Weather Dataset). Examples can be found in Figure 4.

A. DATASET CONSTRUCTION AND LABELING

Specifically, the traffic images are first obtained via multiple traffic cameras and 73,861 traffic images are obtained at this stage. Nevertheless, most of the taken images and their corresponding weather conditions tend to be similar due to the high shot frequency of traffic cameras. After similarity eliminating and quality control, 2,491 images are finally preserved for further precise annotation.

Generally, the traffic conditions are easily affected by the visibility and road weather condition. Taking the high-effect weather into consideration, TWData is categorized into seven classes delicately, i.e., Fog50, Fog200, Fog500, RoadIce, RoadSnow, RoadWet and Sunny. The corresponding descriptions of these seven categories are illustrated as follows.

- Fog50 - The current road visibility is lower than 50m.
- Fog200 - The current road visibility is upper than 50m and lower than 200m.
- Fog500 - The current road visibility is upper than 200m and lower than 500m.
- RoadIce - The road is partly or all covered with ice.
- RoadSnow - The road is partly or all covered with snow.
- RoadWet - The road is wet.
- Sunny - The current weather and road surroundings are sunny.

During label annotation, the images are first labeled by the meteorological stations automatically and then elaborately calibrated by domain experts. Specifically, given a traffic image, the corresponding weather conditions are retrieved in view of the nearest neighbor meteorological stations. These meteorological stations are especially suitable for visibility and snow annotation. However, there might be biases between the given traffic image and the nearest neighbor meteorological station. Manual calibration by domain experts is therefore necessary. Three domain experts are required to check the rationality of the given labels.

B. COMPARISON WITH OTHER WEATHER DATASET

Certainly there are many other weather datasets (abbreviated as PWDatas) in public. Compared with these datasets, TWData has the following advantages.

1) Different from most PWDatas that the images are obtained simply from online web sources, the images of TWData are real world traffic images acquired from traffic management agency. Therefore, TWData is more practicable than other PWDatas.
2) Distinct from PWData, where the weather labels are manually labeled via volunteers, the labels of TWData are firstly labeled automatically via meteorological stations and then rectified by domain experts. It is relatively rough for volunteers to judge the current visibility without any meteorological observation instrument. Consequently, the labels of TWData are more accurate.

TABLE 1. Comparison of current image weather recognition dataset.

Dataset	Reference	Year	Category	Number	Source
Rain Dataset	[15]	2008	Clear, Light rain, Heavy rain	500,000	Vehicle video
EPFL Dataset1	[28]	2012	Sunny, Cloudy, Overcast	1,000	EPFL
WeatherImage	[7]	2014	Sunny, Cloudy	10,000	Flickr, SunData, LabelmeData
MWI Dataset	[8]	2015	Sunny, Rainy, Snowy, Haze	20,000	Flickr, Picasa, Poco, Fengniao
EPFL Dataset2	[14]	2016	Sunny, Cloudy, Overcast	5,000	EPFL
Image2Weather	[34]	2017	sunny,,cloudy, snowy, rainy, foggy, others	183,798	-
MWD	[35]	2017	Cloudy, Rainy, Snowy, Haze, Thunder, Sunny	65,000	Flickr, Google
RFS Dataset	[30]	2018	Rain, Fog, Snow	3,300	Flickr, Pixabay, Wikimedia
Multi-class weather	[36]	2018	Cloudy, Rainy, Shine, Sunrise	1,125	unknown
Five-class Weather	[23]	2019	Sunny, Cloudy, Foggy, Rainy, Snowy	20,000	Moji Weather
TWData	ours	2020	Sunny, Fog50, Fog200, Fog500, RoadSnow, RoadWet, RoadIce	2,941	Highway Camera

TABLE 2. Comparison of state-of-the-art architectures without/with GSM on Multi-class weather dataset.

Model	ShuffleNet		MobileNet		VGG11		VGG13	
	without	***with***	without	***with***	without	***with***	without	***with***
Accuracy	46.54	52.58 ↑	71.76	85.08 ↑	67.50	69.98 ↑	51.33	77.44 ↑
Model	**VGG19**		**ResNet18**		**ResNet34**		**ResNet50**	
	without	***with***	without	***with***	without	***with***	without	***with***
Accuracy	79.22	80.28 ↑	90.94	93.43 ↑	87.39	90.94 ↑	76.02	88.81 ↑

3) TWData has more precise weather labels, e.g., Fog50, Fog200, Fog500, RoadIce, RoadSnow and RoadWet etc, while other PWDatas simply categorize weathers into sunny, cloudy, rainy, foggy or snowy. As a result, the categories of TWData is more precise.
4) TWData is especially constructed for traffic weather recognition while the other PWDatas are designed for either general outdoor scene or in-vehicle images. Hence the applications of TWData is more specific.

A more detailed comparison among TWData and other PWDatas can also be found in Table. 1.

V. EXPERIMENTS

A. DATASET AND TRAINING DETAILS

Taking both of the accessibility and feasibility of PWDatas into consideration, two PWDatas, i.e., WeatherImage [7], and Multi-Class weather [36], and the proposed TWData are employed to demonstrate the effectiveness of the proposed GSM, LSM and GSLSNet. During model training, the widely used SGD optimizer with an initial learning rate of $1e^{-4}$ is employed, and the learning rate is decreased by 0.1 each 10 epochs. The training process stops after 20 epochs without specific illustration.

B. EVALUATION OF GLOBAL SIMILARITY MODULE

1) QUANTITATIVE ANALYSIS

Table. 2 provides a detailed comparison of various backbones without/with GSM, for demonstrating the effectiveness of the proposed Global Similarity Module. Basically, adding GSM to state-of-the-art architectures, e.g., MobileNet [37], ShuffleNet [38], VGG [39] and ResNet [40], improves the weather recognition accuracy obviously. The reason is that the learned feature maps typically comprises a lot of redundant information [42], GSM reduced these disturbances via both channel-wise and spatial-wise filtering.

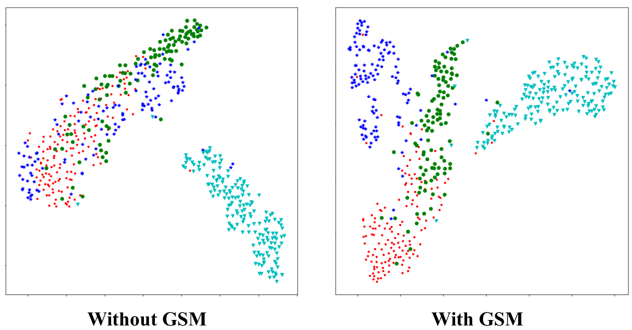

FIGURE 5. An intuitive comparison of without/with GSM effect on Multi-Class Weather dataset.

2) QUALITATIVE ANALYSIS

In order to investigate whether the proposed GSM is capable of enhancing the discriminant of learned features, Figure 5 presents an intuitive comparison of without/with GSM for feature embedding. Specifically, the powerful t-SNE [44] is employed to embed the final *fc* feature into 2D space. Each sample is visualized as a scatter point and the points with same colors belong to the same class. Results show that the feature embedding with GSM is semantically more separable.

C. EVALUATION OF LOCAL SALIENCE MODULE

1) QUANTITATIVE ANALYSIS

As illustrated in section III-B, the purpose of LSM is designed to recognize the weather details on road, therefore, Table. 3 presents a detailed comparison of without/with LSM on

TABLE 3. Comparison of state-of-the-art architectures without/with LSM on TWData.

Model	ShuffleNet		MobileNet		VGG11		VGG13	
	without	***with***	without	***with***	without	***with***	without	***with***
Accuracy	63.76	67.79 ↑	81.54	84.90 ↑	80.87	82.89 ↑	82.55	87.25 ↑
Model	VGG19		ResNet18		ResNet34		ResNet50	
	without	***with***	without	***with***	without	***with***	without	***with***
Accuracy	83.89	89.93 ↑	84.90	86.58 ↑	87.92	90.27 ↑	83.56	85.57 ↑

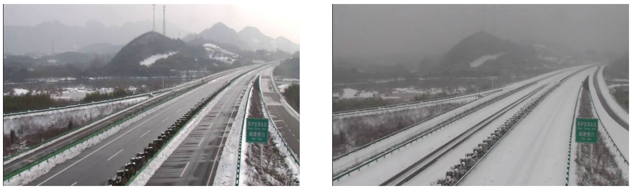
(a) Road Ice (b) Road Snow

FIGURE 6. Examples of LSM effectiveness on TWData, ***Road Ice*** v.s. ***Road Snow***.

TWData. From Table. 3, LSM improves the road weather recognition accuracy. The reasons are also straightforward. Generally, there will be discrepancies between the road weather condition and its corresponding surroundings due to their different heat capacities. Taking the samples of the following Figure 6 for example, the surroundings of both samples are covered with snow. In other words, their global weather conditions are similar. Nevertheless, the left sample is annotated as ***Road Ice*** while the right sample is labeled as ***Road Snow***, and the proposed LSM is capable of recognizing these minor differences.

2) QUALITATIVE ANALYSIS

Furthermore, Figure 7 demonstrates the learned feature maps of without/with LSM restriction considering TWData. Note that there is a minor difference between the input image and the feature map due to the fact that the input image is typically cropped randomly for accurate and ensemble prediction. Specifically, each column represents a given image and its corresponding feature maps. And the brighter the pixel is, the greater the weight it holds. From the results of Figure 7, LSM restricts the network to focusing more on the road conditions. Consequently, the road weather recognition accuracy can be increased especially when there is discrepancy between road itself and its surroundings.

D. EVALUATION OF GSLSNet

Finally, this subsection demonstrates the effectiveness of the proposed GSLSNet compared with other state-of-the-art algorithms. Specifically, Table 4 and Table 5 presents the results on WeatherImage [7], Multi-Class Weather [36] and TWData, resepectively.

Basically, WeatherImage [7] is a commonly used dataset to evaluate the effectiveness of newly proposed methods. As illustrated in Table 1, WeatherImage remains a challenging task even though it contains only two weather classes, i.e., sunny and cloudy. Table 4 and Table 5 provide a detailed comparison of state-of-the-art weather recognition methods and the proposed GSLSNet. From Table 4 and Table 5, the recently proposed convolutional methods outperforms typical machine learning techniques, e.g., Adaboost [7], SVM [7] and Collaborative learning [7], accompanied with hand-crafted weather features. Besides, this section also re-implements other state-of-the-art classification networks, e.g., MobileNet [37], ShuffleNet [38], VGG [39] and ResNet [40] for comparison. Results show that the proposed GSLSNet achieves better recognition accuracy.

TABLE 4. Comparison with state-of-the-art methods on WeatherImage.

Method	WeatherImage [7]
Adaboost [7]	36.4
SVM [7]	41.2
Collaborative learning [7]	53.1
ImageNet+SVM [10]	77.0
WeatherCNN [10]	82.2
Alexnet-MCSVM [20]	80.5
ResNet-MCSVM [20]	90.0
CNN [11]	77.8
CNN+WeatherFeature [11]	84.0
VGG [19]	81.4
MultiTask Weather [19]	87.6
MobileNet [37]	88.1
ShuffleNet [38]	86.1
ResNet [40]	89.6
GSLSNet (ours)	**90.4**

TABLE 5. Comparison with state-of-the-art methods on Multi-Class weather and TWData.

Method	Multi-Class weather	TWData
ShuffleNet [37]	46.5	63.8
MobileNet [38]	71.8	81.5
VGG11 [39]	67.5	80.9
VGG13 [39]	51.3	82.6
VGG19 [39]	79.2	83.9
ResNet-18 [40]	91.0	84.9
ResNet-34 [40]	87.4	87.9
ResNet-50 [40]	76.0	83.6
GSLSNet (ours)	**94.0**	**96.6**

Finally, Table 6 illustrates a detailed comparison of the proposed GSM, LSM and GSLSNet considering both of the network parameters and the time consumption per sample (in terms of TWData). Generally, GSM consists of a one- and a two-dimension convolutional layers. The corresponding parameters are $k^2 C_{in} C_{out}$ and $k^2 C_{in}$ (here $C_{out} = 1$ for the second term), which is far less than the entire network size (refer to Table 6, there is no evident parameter increment with GSM). For LSM, each LSM block comprises five

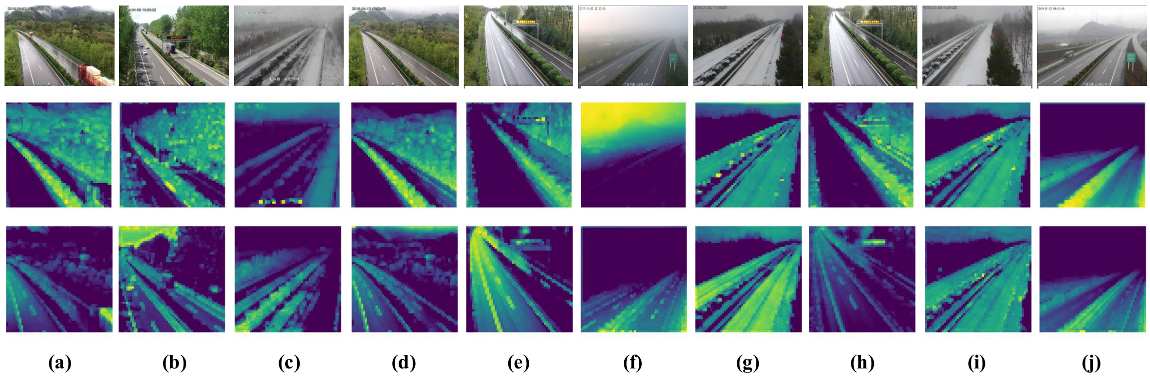

FIGURE 7. The first row demonstrates the original input image. The second row represents feature maps without LSM. The third row illustrates the feature maps with LSM guidance.

TABLE 6. Comparison of different modules implemented on ResNet and VGG in terms of network parameters (#Param.) and time consumption (#Time).

Backbone	Baseline		*with* GSM		*with* LSM		GSLS	
	#Param.	#Time	#Param.	#Time	#Param.	#Time	#Param.	#Time
resnet18	11.18M	1.31ms	11.18M	1.43ms	11.53M	1.99ms	11.53M	2.05ms
resnet34	21.29M	2.19ms	21.29M	2.22ms	21.64M	2.77ms	21.64M	2.79ms
resnet50	23.52M	4.10ms	23.52M	4.19ms	23.87M	4.45ms	23.87M	4.50ms
vgg11	128.80M	3.38ms	128.80M	3.43ms	129.15M	4.78ms	129.15M	4.82ms
vgg13	128.98M	5.43ms	128.98M	5.48ms	129.33M	6.64ms	129.33M	6.66ms
vgg19	139.60M	7.18ms	139.60M	7.29ms	139.95M	8.43ms	139.95M	8.47ms

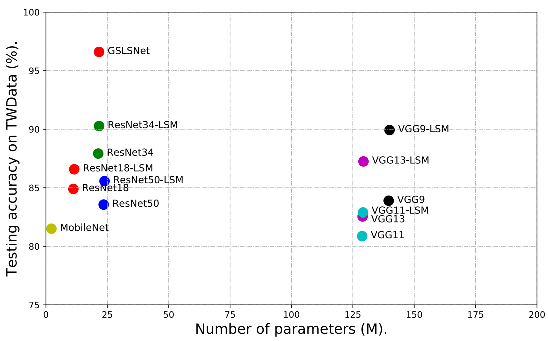

FIGURE 8. Comparison of different GSLSNets in terms of classification accuracy and network parameters. Note that GSLSNet obtain higher accuracy while keeping comparable model complexity.

convolutional layers (four in block and one for dimension reduction) with parameters of size $k^2C_{in}C_{out} \times 4 + k^2C_{in}$. In experiments, LSM stacks four blocks with a slight parameter increase (approximately 0.35M according to Table 6). Additionally, the computation complexity of both GSM and LSM is $\mathcal{O}(WHk^2C_{in}C_{out})$, and a more straightforward time consumption can also be found in Table 6. Figure 8 also presents an intuitive comparison of GSLSNet with various backbones. In conclusion, the proposed GSLSNet obtains higher recognition accuracy with comparable model complexity and time consumption.

VI. CONCLUSION

This paper proposed a new Global Similarity Local Salience network especially for traffic image weather recognition. To achieve that, a Global Similarity module is proposed to identify the general weather description, and a Local Salience module is presented for digging out road weather details. Furthermore, a new weather classification dataset labeled elaborately with accurate weather cues is released. Experimental results on both public dataset and the newly proposed dataset demonstrate the effectiveness of the proposed method.

The future work will consider a joint multi-view learning strategy for weather recognition, due to the large variation of illuminations and viewpoints among images. Also, extracting an effective and robust weather descriptor for images remains a challenging problem. An auxiliary low-rank regularized network is under consideration, for the reason that low-rank regularization has been proved naturally appropriate for robust representation.

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