Received 18 July 2025, accepted 8 August 2025, date of publication 20 August 2025, date of current version 26 August 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3600276

RESEARCH ARTICLE

Enhancing Parking Spot Detection in Extreme Weather Conditions: A Deep Learning Approach With Simulated Weather Augmentation

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This work was supported by Natural Science Foundation of Jilin Province (No. 20240302086GX) and Emerging Frontiers Cultivation Program of Tianjin University Interdisciplinary Center.

ABSTRACT This study tackles the challenge of parking spot recognition in extreme adverse weather by developing an automated scripting tool that enhances real parking images with simulated rain, snow, and fog effects. Experiments using pre-configured network models optimized for specific climatic conditions show that recognition is more effective under single weather conditions than mixed ones. Starting with 30 real foggy images and progressively adding simulated foggy images, the study enriches the dataset without needing large-scale data, improving the model's generalization and adaptability to complex environments. This approach conserves resources and demonstrates efficient learning potential with limited data. Addressing fog's severe visual safety hazards, the study explores the impact of fog density on recognition and assesses deep learning performance in extremely foggy conditions. Experiments establish a critical density threshold for fog, offering decision support for parking in such environments. Despite the human difficulty in recognizing parking spots under heavy fog, deep learning networks show relatively good performance, proving effective when human vision is limited. Supporting code is available on GitHub: https://github.com/Wzxzz/parking-plot.git

INDEX TERMS Convolutional neural network, simulated extreme weather, image processing, image classification, extreme weather.

I. INTRODUCTION

As urbanization accelerates, smart parking solutions are essential to address urban parking challenges and improve traffic efficiency. Fog can severely degrade visual perception systems, affecting parking spot detection and vehicle navigation. Therefore, it is vital to develop intelligent parking systems that remain efficient and stable under adverse conditions. These systems improve parking management and improve detection in low-visibility situations, significantly enhancing driving safety. This necessity drives ongoing innovation to strengthen the robustness and adaptability of the algorithm to real world challenges.

The associate editor coordinating the review of this manuscript and approving it for publication was Joewono Widjaja.

Non-image-based parking spot detection often uses geomagnetic sensors [1] installed directly in parking spaces, but this method is costly and faces scalability issues due to the need for sensor installation and maintenance for each spot. Image-based detection methods have become popular for urban parking challenges because they utilize existing surveillance cameras, reducing additional hardware needs and providing richer data. In 2007, Wu et al. [2] used color histograms spanning three adjacent parking spaces as features for an SVM classifier. By 2015, Almeida et al. [3] employed texture features like LBP and LPQ with SVM classifiers, enhancing performance through ensemble techniques. With the rise of deep learning, Convolutional Neural Networks (CNNs) have dominated parking spot detection. In 2016, Gennaro et al. [4] developed mAlexNet, a binary classification network based on AlexNet, which significantly increases recognition accuracy to over 90% in specific datasets.

Image-based parking space recognition technology excels under extreme conditions, sometimes exceeding human capabilities. These systems maintain stable operation in adverse weather conditions such as heavy rain, snow, and dense fog conditions that often impair human vision, highlighting their reliability and adaptability. Researchers have focused on object detection in harsh weather, with one strategy involving image restoration before applying detection methods. Li et al. [5] analyzed optical scattering in fog and reviewed dehazing technologies over two decades. Gui et al. [6] summarized deep learning-based dehazing algorithms. Yang and Sun [8] proposed a deep dehazing network that combines traditional techniques with deep learning to optimize parameter estimation, effectively merging both approaches.

Due to the lack of large-scale public datasets for vehicles in special weather conditions, researchers often simulate such data using two main approaches. The first is based on physical models, like the optical scattering model [9], which simulates weather effects (e.g., fog, rain) by adjusting parameters without requiring training data. The second approach is data-driven, achieving realistic effects through style transfer techniques using real images. For instance, Zhai et al. [11] combined rain image simulation with adversarial attacks to create realistic rain effects by simulating raindrops through imaging models.

Due to the high computational cost and potential information loss associated with complex image restoration and special weather simulation algorithms, fast and simple simulation methods remain effective and are widely adopted. This paper introduces the RainFogSnow-Simulation (RFS-Sim) algorithm, which adds rain, snow, and fog effects to existing datasets and conducts parking spot recognition directly under these simulated complex weather conditions without prior image restoration. The detailed images are provided in the supplementary material (see Figure S1). **The core idea is to explore and validate that optimized recognition algorithms can effectively detect parking spots even without removing weather influences.** For more details, please see: https://github.com/Wzxzz/parking-plot/blob/master/README.md.

Our research proposes a RainFogSnow-Simulation (RFS-Sim) algorithm to simulate extreme weather conditions and train various models to verify its feasibility. The experimental results indicate that recognition performance under single weather conditions significantly surpasses that under mixed conditions. Focusing on fog due to its substantial visual interference, we utilized 30 real foggy parking spot images and incrementally added simulated foggy images. This approach enriched the dataset and enhanced the model's generalization without the need for extensive data, demonstrating efficient learning in complex scenarios. To address the safety hazards of foggy weather, we explored various fog densities and determined a critical threshold impacting parking spot recognition, providing **decision support** for parking in foggy conditions. Despite human difficulty in these conditions, deep learning networks showed superior recognition performance, highlighting their potential as effective aids under **visually restrictive conditions**.

II. DATASETS

This study used two datasets for analysis. The first is the CNRPark-EXT dataset [4], from which about 8,000 parking spot photos were randomly selected (4,000 with cars and 4,000 without). This extensive library includes 144,965 images captured by nine cameras under various weather conditions, focusing on complex occlusion scenarios and low-light conditions. Additionally, the FoggyParking dataset, containing real images captured in foggy conditions, was used as a supplementary resource. From this dataset, 30 images were selected to examine the impact of fog density on parking spot recognition performance.

III. METHODS AND EXPERIMENTS

The experiments were conducted within the PyTorch framework, utilizing a 3.2GHz AMD R7-6800H CPU and an NVIDIA GeForce RTX 3060 GPU. The OpenCV library was used for RFS-Sim. The CNRPark-Ext dataset and real foggy parking lot images were employed for training and testing. Images were preprocessed to a uniform resolution of 64×64 pixels, and during training, horizontal image flipping was applied with a probability of 0.5 for data augmentation. The network models used included ResNet18 [16], DenseNet121 [15], and our proposed BCFPL [14], with AdamW [12] as the optimizer and cross-entropy loss [13] as the loss function.

A. DEVELOPING A WEATHER-ADAPTIVE PARKING SPOT RECOGNITION AUTOMATION SCRIPT

This section introduces an innovative automated scripting tool developed to simulate real-world scenarios under various weather conditions, thereby enhancing the performance of parking spot recognition systems in diverse and complex environmental conditions. This tool incorporates the RFS-Sim algorithm, enabling the superimposition of various weather effects on a selected original image dataset, including rain, snow, and fog. This process creates a simulated image dataset that extensively covers a wide range of meteorological conditions.

Following the successful implementation of the RFS-Sim algorithm, the script activates multiple weather recognition models for deployment, with this study specifically utilizing the ResNet18, DenseNet121, and BCFPL networks as exemplary cases. Here, the BCFPL model is a lightweight CNN model for low resolution parking space detection [14], which maintains >0.9 accuracy on 7–9 px parking-slot images with just two 7×7 convolutional layers and two fully

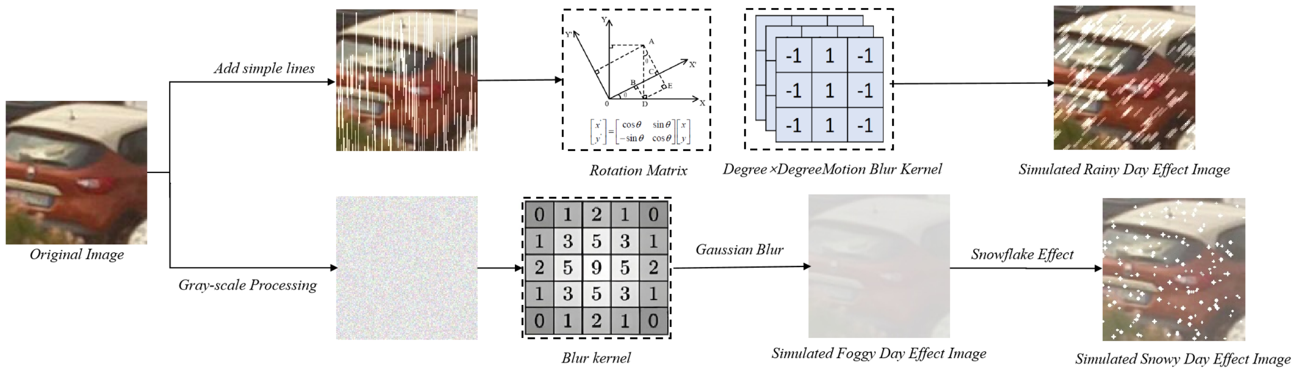


FIGURE 1. Flow chart for RFS-Sim.

connected layers while slashing parameters, computation time, and privacy risk compared with conventional deeper networks such as mAlexNet. These models, leveraging deep learning technology, conduct thorough analyses and identifications of the meteorological conditions within images, accurately distinguishing the specific weather type simulated in the current image. Upon successfully identifying a particular weather condition, the script immediately initiates pre-configured deep network models to execute parking spot recognition tasks on the processed simulated weather mixed dataset, then on scenarios under specific weather conditions. This automated scripting tool has been employed in the experiments described in Sections III-B and III-C, effectively reducing the manual labor time involved in the experimental procedures. The specific operation of this algorithm is as follows:https://github.com/Wzxzz/parking-plot/blob/master/README.md. The detailed algorithm has been included in the supplementary material in the file [algorithm].

B. PARKING SPOT RECOGNITION IN SIMULATED RAIN, SNOW, AND FOGGY WEATHER CONDITIONS

Given the scarcity of parking spot image datasets under complex weather conditions and the challenges these conditions pose to recognition performance, this section is dedicated to exploring the effectiveness of parking spot recognition by simulating rainy, snowy, and foggy weather scenarios.

1) METHODOLOGY

In this study, we processed 8,000 parking spot images from the CNRPark-EXT dataset using RFS-Sim algorithms to simulate three weather conditions: rain, snow, and fog, resulting in 8,000 simulated images for each effect. This created a combined dataset of approximately 24,000 images for training and testing parking spot recognition under specific weather conditions. The dataset comprehensively evaluated the parking spot recognition system's performance in variable weather environments.

As shown in Figure 1, the algorithm for artificial rain effect simulates the blurring effect of falling raindrops relative to the camera sensor using motion blur techniques [17]. This involves applying a motion blur kernel to mimic raindrop trajectories through convolution on the original image. Algorithm 1 shows the process of fog simulation and the other two cases of the algorithm will be provided in the supplementary. To replicate foggy conditions, Gaussian blur [18] is employed to smooth the image and simulate blurred edges of distant objects. By adjusting parameters like the blur radius, the algorithm controls the intensity of the fog effect, simulating environments from light to dense fog. For snow effects, image fusion techniques layer fog and snowflake effects at specific ratios to mimic real snowy environments, achieving a more realistic and comprehensive simulation.

Table 1 shows the comparison of RFS-Sim algorithm and FRG, TPSeNCE algorithm. The whole process of RFS-Sim algorithm only needs one forward reasoning, which is not dependent on; with gradient back propagation and GAN training, the CPU side can reach 40 fps, and higher FPS means faster synthesis. Massive training data, with explicit hyperparameters, users can accurately reproduce the concentration of any rain, fog, and snow without parameter adjustment iteration. At the same time, the method is based on the analytic motion blur kernel, which naturally supports the extension to other bad weather such as snow and fog by replacing the kernel function, and can be seamlessly transplanted to C ++ / OpenCV and other lightweight deployment environment, compared with FRG requiring 20 rounds of backhaul, TPSeNCE relying on a complete set of generation and discriminator framework, this algorithm has significant advantages in speed, stability, portability and multi-weather expansion.

2) EXPERIMENT

The experiments utilized the automated scripting tool that applies the RFS-Sim algorithms. Next, the ResNet18, DenseNet121, and BCFPL network models are automatically invoked to conduct weather-type recognition under learning rates set to 0.0001, 0.00001, and 0.000001. The study explores the parking spot recognition performance under

TABLE 1. Comparison of RFS–Sim, FRG and TPSeNCE Methods.

Metric	RFS-Sim	FRG [11]	TPSeNCE [24]
FPS	40 (CPU forward only)	3 (GPU, 20 backward steps)	30 (GPU forward only)
Raindrop-density control	Explicit counter ρ	Learned sparsity ε_n	Implicit control via contrastive learning (SeNCE)
Direction / blur modelling	Analytic kernel $K(\theta, L)$	STN + learnable kernel	Implicit learning in generator
Iteration times	1	20	1
Portability	Any inference framework	Requires gradient back-prop	Any inference framework
Supported weather	Rain / Snow / Fog	Rain only	Rain / Snow / Night

Algorithm 1 Simulating Fog Effect Algorithm

Input: Input:original image $I_{\text{input}}(x, y)$; Gaussian standard deviation $\sigma = 16.67$;fog spread weight w;fog density weight α;
Output: fogged image $I_{\text{foggy}}(x, y)$;
begin
1. Calculate kernel size: $k_{size} \leftarrow 6\sigma + 1 = 101$
2. Initialize Gaussian kernel $G \leftarrow 0^{101\times101}$, $k \leftarrow 50$
3. **for** $m \leftarrow -k$ *to* k **do**
    4. **for** $n \leftarrow -k$ *to* k **do**
        5. Compute kernel value:
        $G(m+k, n+k) \leftarrow \frac{1}{2\pi\sigma^2}\exp\left(-\frac{m^2+n^2}{2\sigma^2}\right)$
    end for
end for
6.Construct mixed kernel:
$G_w \leftarrow w \cdot G + (1-w)\cdot\delta = G$
7.Initialize blurred image $I_{\text{blur}}(x, y) \leftarrow 0$
8.**for** *all pixel points* $(x, y) \in I_{input}(x, y)$ **do**
    9.Accumulate calculation:
    $I_{\text{blur}}(x, y) \leftarrow \sum_{m=-k}^{k}\sum_{n=-k}^{k} G_w(m, n)\cdot I_{\text{input}}(x+m, y+n)$
end for
10. Blend images:
$I_{\text{foggy}}(x, y) \leftarrow \alpha \cdot I_{\text{blur}}(x, y) + (1-\alpha)\cdot I_{\text{input}}(x, y)$
end

mixed weather conditions compared to single weather conditions. The batch size is set to 64, and the number of training epochs is set to 20.

Experiments illustrated in Figure 2 involved ResNet18, DenseNet121, and BCFPL models with learning rates of 0.00001 and 0.000001. The results show that ResNet18 and BCFPL achieve significantly higher accuracy in single weather conditions than in mixed ones. Although DenseNet121 performs well in mixed conditions, its accuracy is still better in single weather. This is due to the consistency of environmental features like lighting and visibility in single weather conditions, which helps models learn parking slot features more effectively. Mixed weather increases feature diversity, making training more difficult. DenseNet121's deeper architecture allows it to extract more features, maintaining high performance in complex environments. Learning rates also impact performance: a lower rate (0.000001) stabilizes training and improves adaptation to complex conditions but slows convergence, while a higher rate (0.00001) accelerates learning in single weather, enhancing accuracy.

In the bar chart shown in Figure 3, the accuracy comparison across different weather conditions is more clearly illustrated. Under single weather conditions of rain, snow, and fog, all three network models' accuracy is higher than in mixed weather conditions. These results suggest that, in practical applications, to improve the performance of parking slot recognition models, one could employ data augmentation and preprocessing techniques to reduce the diversity of weather conditions or design more robust models to handle variable environments. Additionally, it is essential to fine-tune learning rates and other hyperparameters according to specific application scenarios to achieve optimal model performance.

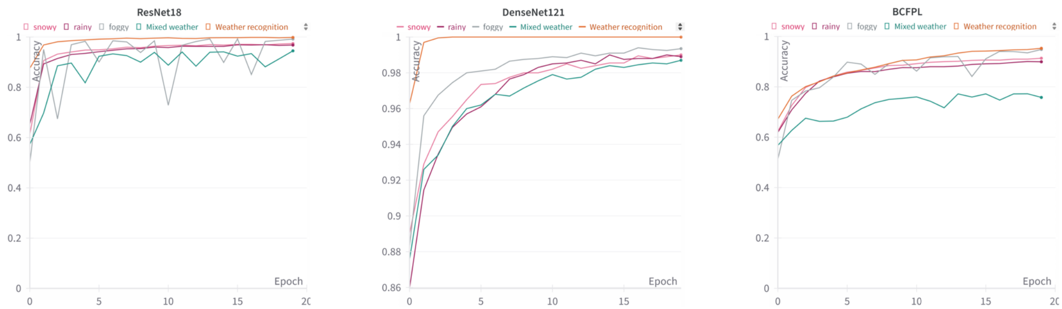
C. ENHANCED DETECTION OF PARKING SPOTS IN REAL FOGGY CONDITIONS USING A SMALL SAMPLE SET

In the current study, the challenges of visual perception in foggy conditions are prominently demonstrated. Although visually, the impact of fog seems to surpass that of other weather conditions, this observation is further corroborated by experimental data. Notably, in Section III-B of the experiment, we observed significant fluctuations in parking spot recognition accuracy under foggy conditions at a learning rate of 0.00001, compared to other weather scenarios. This finding prompted us to focus specifically on parking spot recognition performance in foggy conditions within this study.

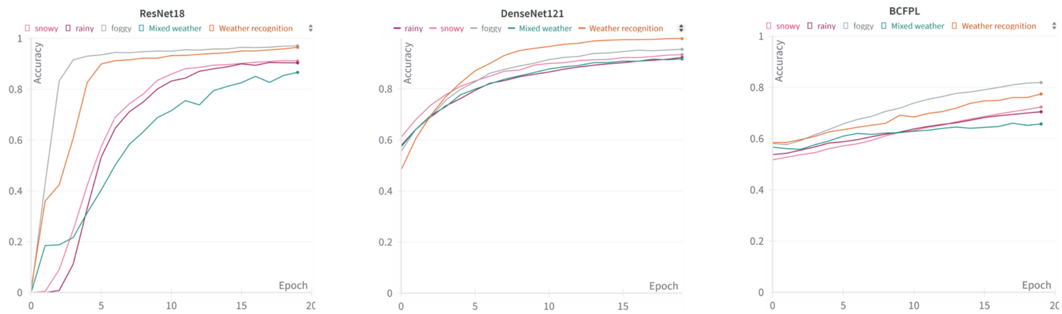
By combining carefully selected small-sample real foggy data with the simulated fog effects algorithm in the RFS-Sim algorithms, this research aims to validate the feasibility of efficient learning using limited data in complex visual environments and to explore strategies for maximizing information extraction from limited data samples. Should this approach be successfully implemented, it would reduce the reliance on large-sample data sets to some extent, thereby saving human resources. This provides valuable practical experience and the theoretical basis for developing efficient visual recognition systems in various complex environments in the future.

1) METHODOLOGY

In this section, we started with 30 real foggy parking lot images—20 for training and 10 for testing. We applied a

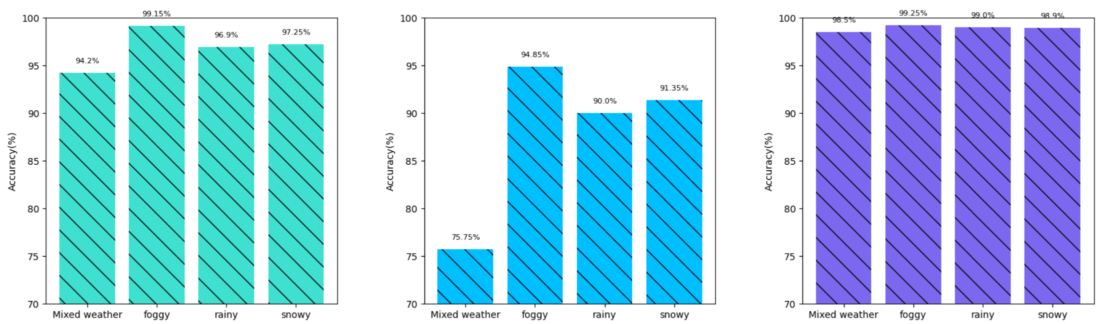


(a) Learning rate=0.00001

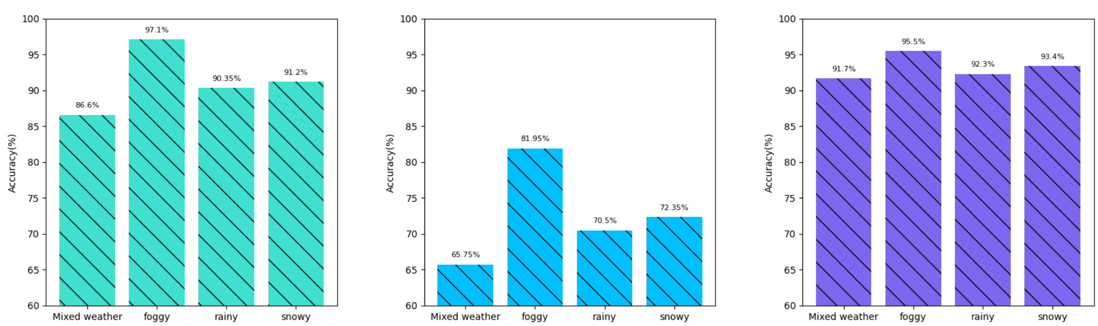


(b) Learning rate=0.000001

FIGURE 2. **Recognition performance of three networks under simulated weather conditions.**



(a) ResNet18-learning rate=0.000001 (b) BCFPL-learning rate=0.000001 (c) DenseNet121-learning rate=0.000001



(a) ResNet18-learning rate=0.000001 (b) BCFPL-learning rate=0.000001 (c) DenseNet121-learning rate=0.000001

FIGURE 3. **Corresponding bar chart of the effects.**

simulated fog effect algorithm to the 20 training images, generating 140 enhanced images with varying fog densities. Figure 4 shows the original images in the first column and the enhanced images with different fog intensities in

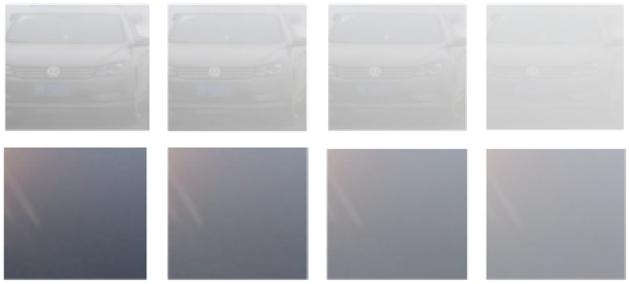


FIGURE 4. Images of parking spots with different densities of fog added.

columns 2 to 4. We then created a series of training and testing datasets by randomly selecting 0, 5, 10, 20, 30, and 50 images from the 140 simulated images and combining them with the original 20 real foggy images. This approach increased data volume and enhanced diversity by integrating real and simulated images, improving the model's generalization ability and robustness in practical applications.

Lastly, we applied Gaussian smoothing techniques to the generated accuracy curves to evaluate the trends in parking spot recognition accuracy. Gaussian smoothing not only smoothed out the accuracy curves but also effectively reduced noise caused by randomness, allowing us to more clearly observe the trend of accuracy changes with the level of data augmentation. This provided strong data support for further optimization of the parking spot recognition model.

2) EXPERIMENT

In this experiment, the batch size is set to 4, and the number of training epochs is set to 60. Within the ResNet18 network and DenseNet121 network frameworks, learning rates of 0.0001 and 0.00001 are employed; under the BCFPL network, a learning rate of 0.00001 is utilized.

The experiments were repeated three times under each learning rate condition, resulting in a total of 15 images. As shown in Figure 5, we only present the result images of the ResNet18 and DenseNet121 networks under a learning rate of 0.00001. The result images of the ResNet18 and DenseNet121 networks under a learning rate of 0.0001, as well as the result images of the BCFPL network under a learning rate of 0.00001, can be found in the supplementary materials as Figures S2, S3, and S4, respectively. The findings reveal the impact of data augmentation strategies on the accuracy of parking spot recognition. It was observed that the inclusion of 5 simulated foggy images did not exhibit a significant change in recognition accuracy compared to scenarios where no simulated images were mixed in.

However, as the number of mixed-in images increased to 10, 20, 30, and 50, a noticeable improvement in parking spot recognition accuracy was observed, indicating that this data augmentation method positively affects accuracy within a certain range. Additionally, this data augmentation technique allows the accuracy of parking spot recognition to reach a stable level more quickly. Under the same experimental conditions, the training process incorporating simulated foggy effect images achieved commendable results by approximately the 30th epoch.

Further analysis revealed that although the initial increase in augmented data volume significantly contributed to accuracy improvements, the accuracy curve subsequently stabilized, indicating that the model performance entered a state of equilibrium. This phenomenon can be attributed to the diminishing marginal effect [22], [23] of effective information brought about by data augmentation. Specifically, as the number of simulated foggy images increased, the incremental information introduced with each addition and its impact on improving model performance tended to decrease, ultimately leading to a plateau in performance enhancement. This result highlights the importance of considering the efficiency and effectiveness of data augmentation strategies when implementing them, choosing an appropriate scale of augmented data to optimize the model training process and enhance recognition accuracy.

Due to deep structure, ResNet18 and DenseNet121 possess superior feature extraction capabilities. When confronted with the visual noise caused by foggy conditions, it can learn more essential and abstract feature representations from these disturbed images. This ability ensures that the model's recognition accuracy remains stable even when applying varying degrees of data augmentation, i.e., introducing more simulated foggy images. This high robustness to subtle variations in input data demonstrates their strong generalization capacity in parking spot recognition tasks, enabling it to effectively process and adapt to visual information under various weather conditions. For the BCFPL, a simple binary classification network model, experiments at a learning rate of 0.00001 demonstrated that mixing 5, 10, 20, and 30 simulated foggy images into the training data could improve accuracy compared to not incorporating any simulated images. When the number of mixed images increases to 50, the BCFPL algorithm becomes unusable.

We conducted a comparative analysis of the three networks across varying learning rates, focusing on the discrepancies in accuracy and the corresponding time expenditures. The outcomes are systematically presented in Table 2. The accuracy figures represent the mean values obtained from three iterations, reflecting the stabilized performance under each specified condition. The time denotes the duration required to achieve the aforementioned levels of accuracy. Figure 6 illustrates the relationship between data quantity and accuracy from Table 2. The dashed lines represent the accuracy saturation value due to marginal diminishing effects, calculated as the average accuracy when introducing 10, 20, 30, and 50 artificial foggy images.

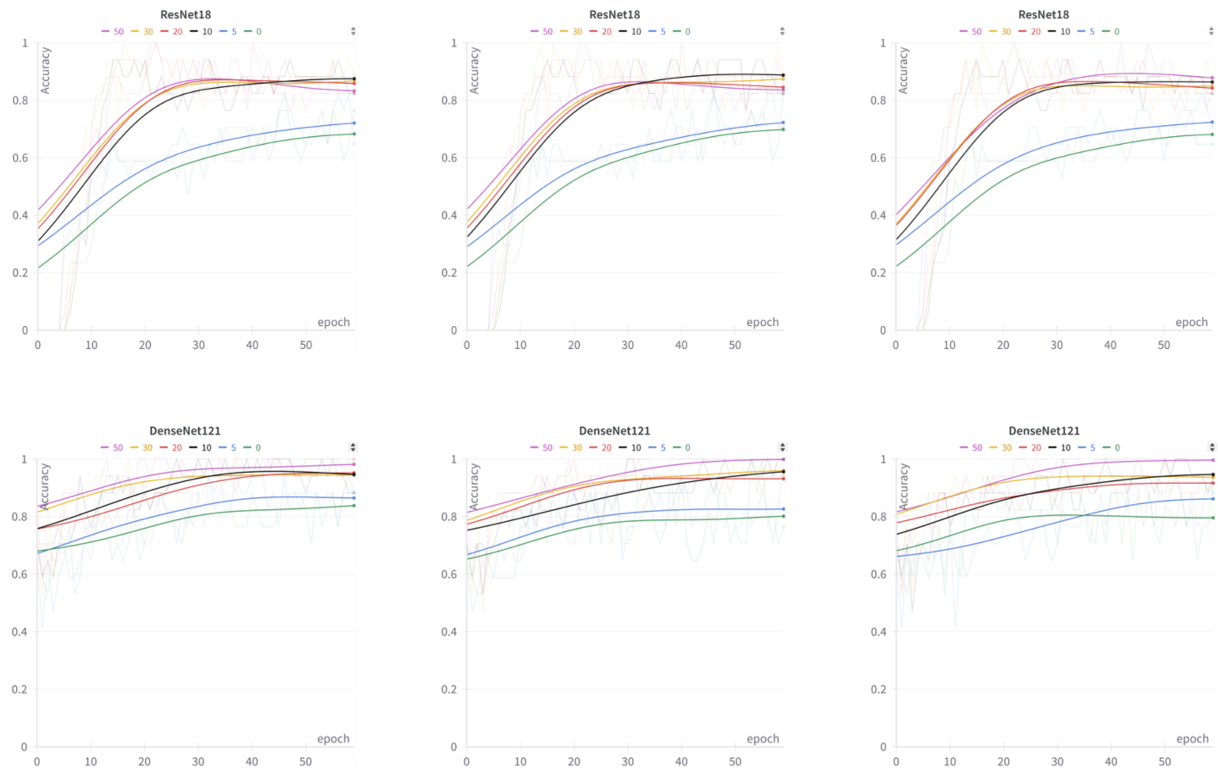


FIGURE 5. **The parking spot recognition performance of the ResNet18 and DenseNet121 networks(Each row consists of three images representing three repetitions of the experiment. The first two rows are conducted at a learning rate of 0.0001, while the last two rows are conducted at a learning rate of 0.00001).**

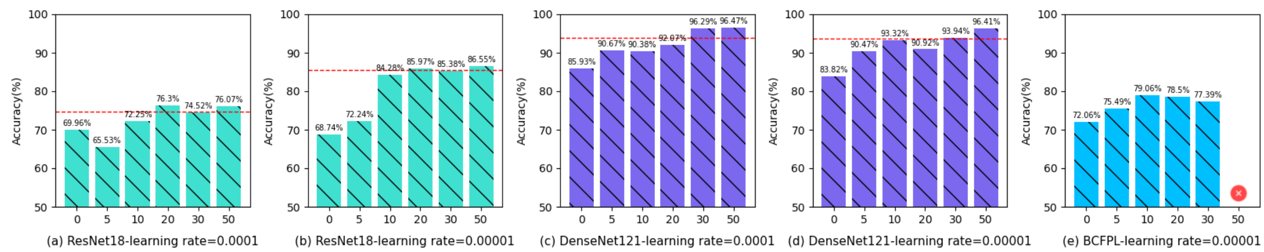


FIGURE 6. **Comparing the ResNet18 network with the BCFPL network at various learning rates reveals differences in accuracy and the time spent.**

From the tables and charts, it is clear that data augmentation at different levels significantly improved parking spot recognition efficiency in terms of both speed and accuracy.

D. CRITICAL CONCENTRATION THRESHOLD UNDER FOGGY CONDITIONS

Considering the significant visual safety hazards presented by foggy conditions, this study also examines the impact of fog density on parking spot recognition effectiveness. This analysis helps to assess the limit of deep learning technologies in identifying parking spots under extremely foggy conditions.

1) METHODOLOGY

This approach uses an artificial fog weather effect algorithm on 8,000 parking spot images from the CNRPark-EXT dataset. Twelve parameters were selected as weights for fog concentration, ranging from 0.96 to 1.0, simulating varying degrees of fog effects from mild to extreme. A weight of 1.0 corresponds to a 100% fog effect, verifying the reliability of the experimental approach. The experimental data points were fitted with a fifth-degree polynomial, chosen for its flexibility and accuracy in capturing complex data trends related to fog concentration and recognition performance. Detailed derivations are included in the supplementary material [3.4.1 methodology].

The fitting process begins by defining an error function to measure the discrepancy between the fitted curve and the actual data points. The error can be expressed as the difference between the accuracy and the polynomial prediction.

By adjusting the coefficients, the error function is minimized. This leads to a system of linear equations from which the optimal solution for the polynomial coefficients can

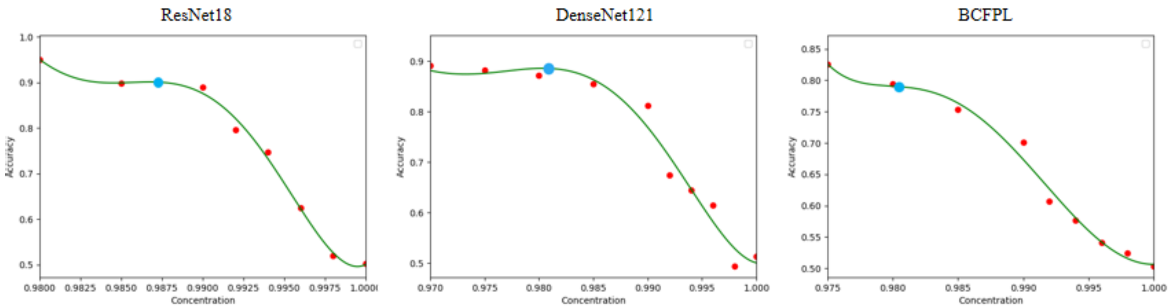


FIGURE 7. The impact of fog density on parking spot recognition using ResNet18, DenseNet121 and BCFPL networks.

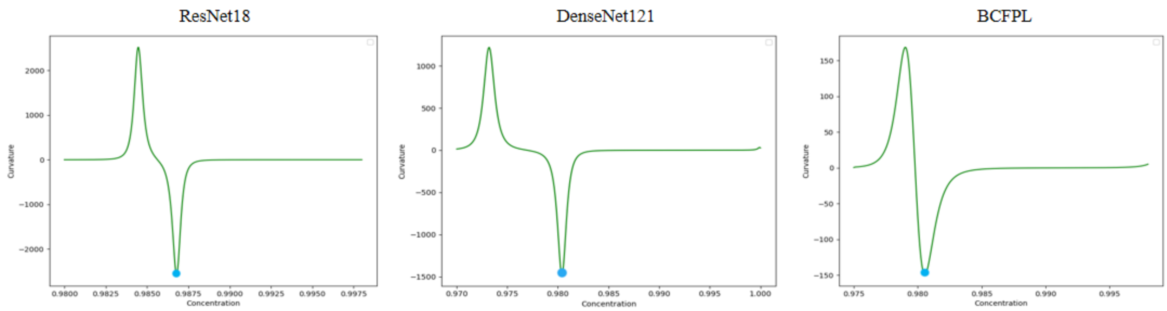


FIGURE 8. The fog density-curvature graph(In this experiment, only points with negative curvature are of practical significance; therefore, only the local minima of the curvature plot are considered).

TABLE 2. Comparing the three networks at various learning rates reveals differences in accuracy and the time spent for model training.

Model	LR	Number	Acc(%)	Time
ResNet18	0.0001	0	69.96	14 s
		5	65.53	16 s
		10	**72.25**	**8 s**
		20	**76.30**	**9 s**
		30	**74.52**	**10 s**
		50	**76.07**	**10 s**
	0.00001	0	68.74	14 s
		5	72.24	16 s
		10	**84.28**	**9 s**
		20	**85.97**	**9 s**
		30	**85.38**	**9 s**
		50	**86.55**	**10 s**
DenseNet121	0.0001	0	85.93	1m 1s
		5	90.67	1m 10s
		10	**90.38**	**30 s**
		20	**92.07**	**30 s**
		30	**96.29**	**29 s**
		50	**96.47**	**30 s**
	0.00001	0	83.82	1m 4s
		5	90.47	1m 13s
		10	**93.32**	**30 s**
		20	**90.92**	**30 s**
		30	**93.94**	**30 s**
		50	**96.41**	**29 s**
BCFPL	0.00001	0	72.06	8 s
		5	**75.49**	**8 s**
		10	**79.06**	**8 s**
		20	**78.50**	**9 s**
		30	**77.39**	**9 s**
		50	59.36	11 s

be obtained. With these optimal coefficients, the fitting curve is then derived. Analyzing the curve by calculating its first and second derivatives provides insights into data trends and characteristics. The second derivative helps assess changes in curvature. By introducing varying densities of fog to parking spot images, we aim to identify the critical point where recognition effectiveness declines significantly. We define positive curvature as the area above the fitted curve and negative curvature below it. Positive curvature indicates the curve is concave upwards, while negative curvature indicates concave downward. Only the negative curvature portion is relevant for determining fog concentration thresholds, as it reflects the scenario where increased fog leads to decreased recognition accuracy, representing the performance deterioration phase.

2) EXPERIMENT

The experiment utilizes the foggy weather parking spot dataset processed through the RFS-Sim algorithms, as described in Section III-A. The batch size is 64, with 30 training epochs, and the learning rate is set to 0.000001. To analyze the data more precisely, we focused exclusively on the segments where the impact of fog concentration on parking spot recognition performance was significant under two different networks while disregarding the parts where the influence was minimal.

As shown in Figure 7, recognition accuracy declines as fog density increases, with ResNet18 and DenseNet121 showing smaller drops compared to BCFPL due to their more complex structures. Curvature analysis in Figure 8 identifies critical fog density thresholds: for ResNet18, the minimum curvature is -2566.96 at a fog density of 0.987, for DenseNet121 it's −1473.98 at 0.9804, and for BCFPL it's −148.54 at 0.981. These thresholds mark the point where recognition performance declines sharply, highlighting the networks' varying abilities to handle visual blurriness.

Additionally, in Supplementary Figure S5, we present parking spot images with fog density weights of 0, 0.96, 0.97, and 0.98 added sequentially. As the concentration increases, it becomes difficult for the human eye to distinguish the presence of parking spots. The visual blurriness and the decline in contrast under such conditions severely impact human visual recognition capabilities. However, deep learning networks still demonstrate relatively good recognition performance in these extreme environments.

Hence, applying deep learning technology in foggy conditions for parking spot recognition showcases its capability to handle complex visual recognition tasks and offers an effective supplementary solution when human vision is limited.

IV. CONCLUSION AND DISCUSSION

This study contributes to the development of parking space recognition systems under extreme weather conditions and demonstrates the potential of deep learning in addressing complex weather challenges. By integrating simulated weather effects and focusing on specific issues related to extreme weather, research provides a new direction for improving the stability and accuracy of image-based parking space recognition systems in urban environments. Furthermore, although this study's experiments were conducted in an offline environment, the proposed RFS-Sim data augmentation pipeline, automated scripting framework, and multi-model fusion strategy offer direct applicability to real-world parking lot scenarios. The core inference code can be ported on edge devices such as camera in the parking lot, this enables efficient parking spot detection at the edge, with results uploaded via MQTT/HTTP protocols to cloud or local servers, and further integrated with parking management systems for a complete ''detection–billing–guidance'' workflow. Additionally, the automated scripts allow for regular batch acquisition and annotation of the latest surveillance data, supporting continuous adaptation through federated or periodic cloud-based re-training to handle variations in camera views, parking space markings, and real-world extreme weather occurrences, thus maintaining robustness and practicality over time. Therefore, this research not only demonstrates technical feasibility under challenging weather but also lays a solid foundation for future engineering deployment and large-scale application.

This study enhances parking spot recognition by simulating adverse weather effects like rain, snow, and fog on real images. Using an automated tool and networks like ResNet18, DenseNet121, and the proposed BCFPL model, experiments show that recognition accuracy is higher under single weather conditions compared to mixed conditions. A small-sample approach effectively improves model generalization without large datasets, conserving resources. The research also identifies a critical fog density threshold, aiding decision-making in foggy conditions. Despite the challenges for human observers, deep learning networks perform well, proving reliable in visually difficult scenarios.

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