Identification of nighttime urban flood inundation extent using deep learning

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Abstract. With the acceleration of urbanization, the disaster of urban flooding has had a serious impact on urban socio-economic activities and has become one of the important factors restricting social development in China. Accurate and timely identification of urban flooding extents is crucial for decision-making. Traditional remote sensing technologies are often limited by environmental factors, making them less suitable for application in complex urban terrains. With the increase in urbanization and the development of emerging technologies, video imagery has become a significant data source with great potential for urban flood identification. However, existing research has primarily focused on flood extent identification in daytime scenarios, often neglecting the nighttime, a period of high flood occurrence. In this study, we propose an efficient model (NWseg) to identify flood extents in nighttime scenes.~~The development of emerging technologies and the increase in urbanisation have led to a significant increase in the number of surveillance devices within cities, while the development of deep learning techniques has led to their widespread application in various fields. Deep learning methods using video images as a data source provide a new technical methods for intra-urban waterlogging recognition. However, current research mainly focuses on waterlogging recognition in daytime scenes, often ignoring nighttime, a time of high waterlogging incidence.To address these challenges faced by flooding recognition in the nighttime, this study proposes a deep learning model—NWseg—to achieve the recognition of the extent of waterlogging at night.~~ Initially, we constructed a nighttime flood inundation dataset consisting of 4,000 images.~~a dataset of 4,000 images of nighttime urban flooding.~~ Subsequently, MobilenetV2 and ResNet101 networks were used to replace the DeepLabv3+ backbone network and compared with the NWseg model. Next, the NWseg model was compared with ResNet50-FCN, LRASPP and U-Net models to evaluate the performance of different models in nighttime urban flooding extent identification. Finally, we verified the applicability and performance differences of each model in specific environments. Overall, this study successfully

demonstrates the effectiveness of the NWseg model for nighttime urban flooding extent identification, providing new insights for nighttime flood monitoring in cities.~~the applicability and performance differences of each model in specific environments were verified. In conclusion, this study successfully demonstrates the effectiveness of the NWseg model for nighttime urban flooding identification and provides new insights for nighttime urban flooding identification.~~

Keywords: Deep learning, Nighttime flooding extent identification, Urban flooding, NWseg

1 Introduction

In recent years, extreme rainfall events have been occurring frequently in the context of complex climate change (Burn and Whitfield, 2023; Kim et al., 2024). Concurrently, with the acceleration of urbanization processes, the proportion of impervious surfaces has been continuously expanding, resulting in serious urban flooding issues in many cities worldwide (Ghosh et al., 2024; Liu et al., 2023; Kundzewicz et al., 2019)~~(Xue et al., 2023)~~. Urban flooding often coincides with multiple compounded disasters and may even trigger secondary calamities, posing serious threats to the safety of urban residents, the normal operation of city functions, and sustainable development. This exacerbates the vulnerability of urban socio-economic system (Gu et al., 2025; Visser, 2014; Zheng et al., 2014)~~(Luo et al., 2020)~~. Therefore, achieving real-time and effective identification ~~monitoring~~ of urban flooding extent has become a critical issue that urgently needs to be addressed.

Remote sensing technology has made significant advancements in the field of urban flood identification~~monitoring~~, providing new perspectives for flood disaster~~s~~ identification through high spatial, temporal and spectral resolution data (Bofana et al., 2022)~~(Hao., 2022)~~. However, despite its excellent performance at the macro scale, remote sensing technology has limitations in urban area monitoring. Due to the limitations in temporal resolution and the impact of cloud cover and atmospheric variations, remote sensing technology struggles to capture the dynamic changes of urban flooding, making real-time identification of rapidly evolving flood events challenging (Mason et al., 2012).~~Due to insufficient temporal resolution as well as the influence of cloud cover and changing atmospheric conditions, remote sensing techniques have difficulty in capturing subtle topographic changes within cities, and are unable to monitor fast-changing flooding events in real time (Gao., 2023).~~ In addition, the complexity of the urban environment, especially the dynamic changes of small-scale water bodies and localized waterlogging, further increases the difficulty of remote sensing technology in urban flooding ~~flood~~ extent identification~~monitoring~~. Therefore, an intelligent and real-time urban flood monitoring method is urgently needed to achieve more precise flood identification.

With technological advancements, the emerging fields of deep learning and computer vision have matured and engaged in interdisciplinary collaborations, achieving significant performance~~remarkable results~~ that offer new technical approaches for urban flood identification (Choi and Yoo, 2023). Particularly in image segmentation~~recognition~~, deep learning's advantages

in extracting global features and contextual information make it highly promising for inundation detection (Liu et al., 2020)~~(Liao., 2023)~~. Simultaneously, the increasing level of urbanization has led to the widespread deployment of video surveillance devices across urban areas, particularly in highly urbanized areas (Muhadi et al., 2024; Hao et al., 2022)~~along city roads, where they are ubiquitous~~. During rainfall, these cameras can fully record the flooding process, providing real-time reflections of road inundation changes (Wang et al., 2024)~~(Wang et al., 2024; Yang et al., 2022; Cheng et al., 2018)~~. Therefore, combining deep learning with traffic cameras can effectively achieve the identification of urban flooding extent.

Existing research has demonstrated that deep learning excels in segmenting inundated areas. Sarp et al. (2020) ~~(Bai et al., 2021) utilized the YOLOv2 object detection model to extract water accumulation features from images collected by Xi'an University of Science and Technology, achieving an average recognition accuracy of over 85% through multiple model training sessions, demonstrating the precision of this method for inundation area extraction. (Wang et al., 2021) classified road images into four categories—background, dry surface, inundated area, and slippery surface—and used the Res-UNet+ semantic segmentation network to handle different lighting and scene conditions, achieving an Mean Intersection over Union (MIoU) of 90.07%, outperforming traditional classification methods. (Sarp et al., 2020)~~ applied the Mask R-CNN model to automatically detect and segment floodwaters in urban, suburban, and natural scenes, achieving 99% accuracy in the detection phase and 93% in the segmentation phase. ~~(Sazara et al., 2019)~~Sazara et al. (2019) used a deep learning approach to detect standing water on urban roads, in which a pre-trained VGG-16 network was used in the classification phase and a full convolutional neural network was used in the segmentation task, and compared it with the traditional classifier and extraction algorithms with manually-designed features, and the results showed that the deep learning approach has a more obvious advantage in both the recognition and segmentation of standing water. Wang et al. (2024) used a deep convolutional neural network (DCNN) for urban flood extent recognition based on video images acquired from surveillance cameras. Zeng et al. (2024) proposed a DeepLabv3+ based flood image recognition method, which effectively improves the model performance through image enhancement and the introduction of the super-resolution generative adversarial network. However, current research focuses on daytime scenes, and the existing datasets lack diversity to cover flooding scenes at night or under complex weather conditions. Meanwhile, some algorithms underperform when processing images in low-light or adverse conditions, making flood extent identification at night or in challenging weather a technical challenge. This limitation underscores the urgent need for accurate nighttime flood extent identification~~monitoring~~ and the necessity for algorithm improvements and dataset expansion.

To address the above challenges, this study proposes an efficient method for nighttime urban flood extent identification. First, an urban flood inundation dataset for nighttime scenes is constructed to provide sufficient sample support for model training. Subsequently, a NWseg model for nighttime image segmentation is proposed, which combines a Content-Light Splitter with a Dual-Feature Integrator to enhance the model's performance in identifying flooding extent in low-light environments. Meanwhile, given that the data are mainly sourced from urban road surveillance systems, the method is

particularly suitable for street (Street) and local area (District) scale flood detection. Finally, the robustness and performance advantages of the NWseg model in nighttime urban flood recognition are verified through experimental comparison with mainstream segmentation models. This study not only promotes the development of nighttime urban flood recognition technology but also provides theoretical support and practical experience for future deep learning research in low-light environments using nighttime.~~For this specific scenario, we propose the NWseg model for waterlogging recognition in nighttime, inspired by the method introduced by (Wei et al., 2023). The problem of insufficient model recognition accuracy in nighttime scenes is effectively solved by two core components, Semantic-Oriented Disentanglement (SOD) and Illumination-Aware Parser (IAParser) (Wei et al., 2023). On this basis, this study constructs an urban flooding dataset for nighttime scenarios, based on which the model is trained to improve the model's ability to recognise the extent of urban flooding in nighttime environments.~~

Totally, the main contributions of this paper are as follows:~~This study aims to enhance urban flood extent recognition in nighttime scenes by utilizing advanced semantic segmentation techniques and a comprehensive all-nighttime dataset, addressing the current limitations in both datasets and methodologies. More specific, our aims are as follows:~~

(1) Contributed a method for nighttime urban flooding extent identification~~assessing urban flooded areas~~ based on urban surveillance cameras, aiming at realizing efficient assessment of nighttime urban flooding areas and filling the gaps of research in this field at this stage.~~in response to common challenges in the field of nighttime urban flooding identification.~~

(2) To support the generalization ability of the model in complex nighttime environments, this study constructs a nighttime flood inundation dataset covering a variety of nighttime scenarios (e.g., different weather, illumination intensity, and urban structure), which provides diverse sample resources required for training and testing.~~A comprehensive and representative nighttime urban flooding dataset is constructed. It covers a wide range of nighttime scenes, including different weather conditions and city layouts, providing a rich resource for training and testing semantic segmentation models.~~

(3) Replace the original DeepLabv3+ model network backbone with MobilenetV2 and ResNet101 networks and verify the effect of different network backbones on the performance of the Deeplabv3+ model.~~Replacement of the original DeepLabv3+ model network backbone with MobileNetV2 and Resnet101 networks is used to verify the performance impact of different network backbones on the DeeplavV3+ model through ablation experiments.~~

(4) An urban flood identification~~A waterlogging recognition~~ model NWseg for nighttime scenarios is proposed~~contributed~~, and the significant advantages of the model in terms of robustness, effectiveness and practicality are verified by comparing with other existing models, which advances the research and development of nighttime urban flooding extent identification~~flood recognition~~.

2 Model

2.1 Nighttime Urban Segmentation Model

Flood segmentation faces significant challenges in nighttime scenes. Insufficient illumination and interference from complex artificial light sources such as streetlights and headlights result in blurring of texture, edge, and color information in flooded regions, further exacerbating the difficulty of the segmentation task and severely affecting the robustness and accuracy of the model. To address this challenge, this study proposed a flood extent recognition model specifically designed for low-light nighttime scenes - the NWseg model, which aims to alleviate the impact of low illumination and complex lighting conditions on segmentation performance. As shown in Figure 1, the NWseg model consists of two key modules: Content-Light Splitter (CLS) and Dual-Feature Integrator (DFI).

The design of the CLS module is based on the Retinex theory, which states that an image can be decomposed into a pixel-by-pixel product between a light-independent reflectance component (reflectance) and a light-related illumination component (illumination) (Land. 1977). Based on this principle, the CLS module decomposes the night image into a "reflectance map" and an "illumination map," which represent the inherent semantic information of the flood area and the lighting distribution in the scene, respectively (Wei et al., 2023). Subsequently, a semantic guidance mechanism is introduced to optimize the semantic segmentation loss during training (i.e., the difference between predicted pixel-level class labels and true labels), enabling the reflectance map to learn clearer boundaries and stronger semantic expression, thereby achieving accurate identification of the true contours of the flood areas. In addition, to addressing the interference from artificial light sources (such as car headlights and traffic lights), NWseg further designs the DFI module to enhance segmentation performance by adaptively fusing reflectance and illumination features. The DFI module first encodes the reflectance and illumination features and then constructs an attention mechanism that learns the degree of dependency between each pixel and the two feature types, enabling adaptive feature-weighted fusion at the pixel level (Li et al., 2024). This process adopts a pixel-wise weighting strategy, effectively enhancing the model’s ability to recognize light-dominated categories. Finally, the DFI module introduces a dual semantic supervision mechanism: it not only applies semantic segmentation supervision to the fused output but also imposes semantic loss on the illumination channel separately, to enhance its independent discriminative ability and improve the model's overall generalization capability (Wei et al., 2023).

In summary, NWseg, through the collaborative design of the CLS and DFI modules, demonstrates superior semantic understanding and segmentation ability in complex nighttime lighting scenarios. It shows significant robustness and recognition advantages, particularly in high-reflection, low-contrast, and locally overexposed areas.

~~Nighttime scenes are typically characterized by low-temperature illumination and complex artificial light sources, which lead to changes in object appearance due to variations in lighting conditions. This reinforces the entanglement between light-invariant reflectance and light-specific illumination, making it challenging to extract discriminative features for semantic~~

segmentation. Based on this background, proposed a nighttime waterlogging recognition model —NWseg, specifically designed to cope with the problem of degraded segmentation performance due to insufficient illumination and complexity in nighttime scenes (Wei et al., 2023).

The paradigm consists of two core steps: decoupling and parsing. The inference is shown in Figure 1. In the decoupling phase, NWseg decomposes the input image into light-invariant reflectance and illumination-specific components. The designed SOD framework decomposes the image into illumination-independent reflectance components and light-specific components by semantically supervising the training of the de-entanglement module. It utilises Retinex theory to ensure that stable light-invariant reflectance is extracted under complex illumination conditions, which enhances the semantic recognition in the subsequent parsing phase. The parsing phase then extracts illumination features using an Illumination-Aware Parser (IAParser), which quantitatively evaluates the semantic information contained in the illumination by using a pyramid pooling module and a convolutional layer to construct an attention mask. The final segmentation result is obtained by combining reflectance and illumination features. The model effectively copes with the complex and variable lighting challenges in nighttime scenes through the dual mechanism of decoupling and parsing, and significantly improves the performance of semantic segmentation (Wei et al., 2023).

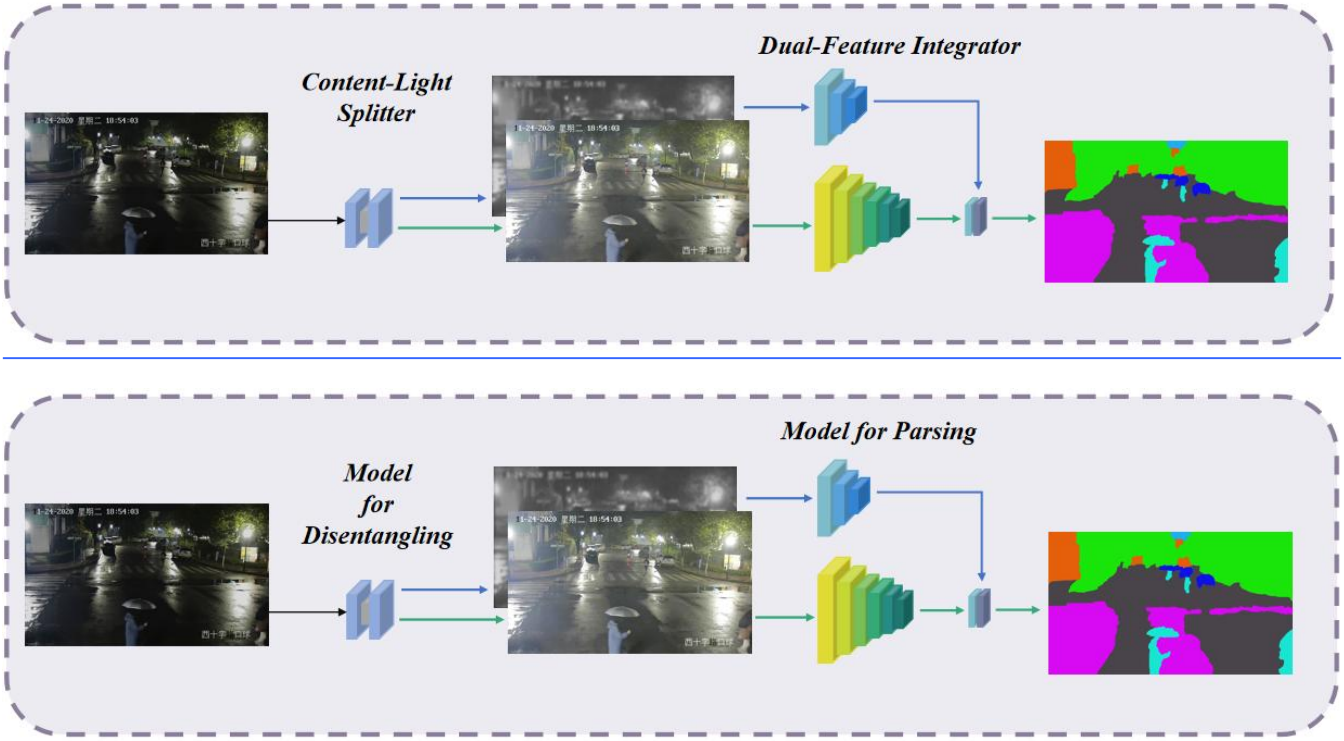


Figure 1: NWseg model inference process

2.2 Typical semantic segmentation model

DeepLabv3+ is an advanced model in the field of image segmentation, which significantly improves the accuracy and detail processing ability of image segmentation by introducing an encoder-decoder structure (Bai et al., 2023; Peng et al., 2023). The encoder part is responsible for extracting the high-level features of the image, while the decoder focuses on recovering

the details of the image, thus realizing a more fine-grained segmentation effect (Fu et al., 2021). The model also employs the techniques of void convolution and Atrous Spatial Pyramid Pooling (ASPP), which can effectively capture the multi-scale information of the image and improve the processing capability of complex scenes and object boundaries (Wang et al., 2024; Peng et al., 2024). Cavity convolution enables the model to capture a larger range of image information without increasing the computational effort by introducing voids in the convolution kernel. It is particularly helpful in capturing the relationships between distant objects in an image (Yu et al., 2017). Atrous Spatial Pyramid Pooling (ASPP), on the other hand, enhances the recognition of objects of different sizes by using different scales of null convolution to extract multiple levels of image features, which helps the model to focus on both detailed and global information (He et al., 2014). In addition, DeepLabv3+ uses Xception as the backbone network, combined with depth-separable convolution to improve computational efficiency. Depth separable convolution divides the traditional convolution operation into two steps: first, each image feature is processed independently, and then the results are combined (Zhang et al., 2023). This approach effectively reduces computation and storage requirements, allowing the model to operate more efficiently while maintaining high accuracy. However, due to its relatively complex network structure, DeepLabv3+ is still slow in the inference stage.

~~The DeepLab network series is an improved set of models based on fully convolutional neural networks (FCNs). These methods effectively enhance the receptive field of convolutional kernels to acquire multi-scale feature information, thereby optimizing the spatial accuracy of segmentation results (Feng et al., 2023; Chen et al., 2024). The network models mainly utilize techniques such as atrous convolution and atrous spatial pyramid pooling (ASPP) to extract multi-scale features and capture contextual information from images. The series includes DeepLabV1, DeepLabV2, DeepLabV3, and DeepLabV3+. DeepLabV3+ is the latest version in the DeepLab series (Li et al., 2024; Peng et al., 2024; Ma et al., 2024; Zhang er al., 2023); it introduces an encoder-decoder structure by adopting DeepLabV3 as the encoder and adding a decoder to form a new model. The Xception model is applied to the segmentation task, extensively using depthwise separable convolutions within the model. However, this network still has limitations in modeling long-range dependencies, insufficient handling of class-imbalanced data, and higher latency for real-time applications. While DeepLabV3+ combines the spatial pyramid pooling module and encoder-decoder structure in deep neural networks to achieve fine segmentation of object boundaries, it remains constrained in modeling long-range dependencies, dealing with class imbalance, and reducing latency for real-time applications (Li et al., 2023; Zhang et al., 2024; Tao et al., 2023).~~

To enhance the segmentation performance of DeepLabv3+ in urban flood scenes, this study designs a series of controlled experiments, systematically modifying or removing network components to verify the effectiveness of different backbone networks (i.e., ablation studies) and compares the results with the NWseg model.~~designed ablation experiments to verify the effectiveness of different backbone networks and compared them with the NWseg model.~~ First, experiments were conducted on the original, unmodified DeepLabv3+ network as a baseline model. Then, we replaced the original DeepLabv3+ backbone network with the lightweight MobilenetV2, constructing an improved model (denoted as

MobilenetV2-DeepLabv3+). MobilenetV2 is structurally optimized to compress the feature information while retaining the key information as much as possible, thus achieving a lightweight model while maintaining high accuracy (Jin et al., 2023).~~MobileNetV2 optimizes the number of model parameters by introducing a linear bottleneck layer and inverted residual structures, ensuring a lightweight model while maintaining high accuracy (Jin et al., 2023).~~ Finally, we replaced the backbone network of DeepLabv3+ with the residual neural network ResNet101 to form another improved model (denoted as ResNet101-DeepLabv3+). ResNet101 adopts the residual connection mechanism so that part of the feature information can bypass the intermediate layer and be transmitted directly, which avoids the problems of "learning stagnation" or "training instability" during the training process ~~ResNet101 leverages a residual learning mechanism, allowing input information to bypass certain layers, addressing gradient vanishing and explosion issues during deep network training. This enhances the model's ability to capture spatial depth and details, ultimately improving the accuracy and robustness of flood area recognition~~ (Wang et al., 2024)~~(Yang et al., 2023; Wang et al., 2024)~~.

The Fully Convolutional Network (FCN) is a deep learning model that divides images into different regions by assigning a specific label to each pixel. Traditional deep learning models typically provide only an overall classification result for an entire image. In contrast, FCNs improve upon these models by replacing the fully connected layers with convolutional operations, enabling the network to handle input images of any size and produce detailed, pixel-level predictions (Yang et al., 2017). FCNs progressively compress the spatial dimensions of the image to extract essential information and then restore the original size to achieve precise localization of different regions (Zhao et al., 2018). Additionally, FCNs combine information from both shallow and deep layers, further enhancing segmentation accuracy in complex areas, such as flood boundaries. In this study, ResNet50 was selected as the backbone network for FCN, referred to as ResNet50-FCN. ResNet50 is a deep neural network that effectively alleviates the gradient vanishing problem during training, improving stability and efficiency. By combining the depth of ResNet50 with the flexibility of FCN, the proposed model enhances the accurate detection of inundated areas in complex environments.

~~The Fully Convolutional Network (FCN) is an architecture specifically designed for semantic segmentation by replacing the fully connected layers of traditional Convolutional Neural Networks (CNNs) with convolutional layers. This allows FCNs to process input images of arbitrary sizes and perform accurate pixel-wise classification. FCNs extract features through convolutional layers, reduce feature dimensionality via pooling layers, and restore feature map sizes using upsampling layers, achieving precise pixel-level segmentation. Techniques such as bilinear interpolation are employed to preserve image details (Zhao et al., 2018). Additionally, skip connections in FCNs effectively fuse shallow and deep feature information, improving segmentation accuracy. In this study, ResNet50 is adopted as the backbone network for FCN, denoted as ResNet50-FCN. ResNet50 utilizes a residual learning mechanism to address gradient vanishing issues during deep model training, maintaining training stability and efficiency while enabling greater depth. The multiple residual blocks in ResNet50 capture rich multi-scale features, adapting to structures from coarse to fine. Its skip connections preserve the~~

~~detailed information that can be lost during upsampling, ensuring high-precision semantic segmentation. Combining the depth of ResNet50 with the flexibility of FCN, this model enhances the accurate detection of inundated areas in complex environments.~~

LRASPP (Lightweight Refine Atrous Spatial Pyramid Pooling) is a lightweight model designed for image segmentation tasks. The model adopts MobileNetV3 as the backbone network for extracting the base features of an image and fuses shallow features to enhance the retention of detailed information. To further enhance the inference efficiency, LRASPP reduces the number of convolutional operations in the structural design and streamlines the feature channels to effectively reduce the computational complexity. Ultimately, the model restores the feature map to the same size as the input image through the upsampling operation to achieve accurate prediction of each pixel category ~~The LRASPP network is a lightweight semantic segmentation model designed for efficient operation on resource-constrained devices such as mobile and embedded systems. It simplifies the classic ASPP (Atrous Spatial Pyramid Pooling) module, retaining its ability to capture multi-scale contextual information while significantly reducing computational complexity and memory usage. By leveraging depthwise separable convolutions to reduce the number of parameters and incorporating detailed information from lower-level features, LRASPP achieves a balance between model efficiency and accuracy. The model employs MobileNetV3 as the lightweight backbone to extract image features and generate multi-scale feature maps. It also simplifies the original ASPP module by capturing multi-scale contextual information through atrous convolutions and fusing low-level detailed features to improve segmentation accuracy. By reducing convolutional layers and the number of channels, the network significantly lowers computational complexity. The final output is upsampled to match the input image size, ensuring both efficiency and accuracy in segmentation tasks~~ (Tang et al., 2024).

U-Net is a deep learning model commonly used for image segmentation tasks, and its structure is mainly composed of two parts: encoder and decoder (Siddique et al., 2021). The encoder is responsible for gradually reducing the image size and extracting key features, while the decoder recovers the detailed information by gradually enlarging the feature map, thus realizing the accurate classification of each pixel. In addition, to compensate for the information lost during the process of reducing the image size, U-Net introduces a jump-join mechanism, which passes the features extracted at different stages in the encoder directly to the corresponding decoder stage (Sengupta et al., 2025). This design enables the model to better preserve the detailed features in the image while maintaining overall semantic understanding~~U-Net is a classic network architecture for image segmentation, built on fully convolutional networks (FCNs). It utilizes skip connections to directly concatenate features from downsampling and upsampling layers along the channel dimension, effectively integrating information from different layers. U-Net features a symmetrical encoder-decoder structure, with a left downsampling path, a right upsampling path, and intermediate skip connections. The downsampling path resembles traditional CNN architectures, consisting of alternately stacked convolutional and pooling layers, while the upsampling path uses transposed convolution to progressively restore the feature maps to the original image resolution (Zhang et al., 2023). Shallow features primarily~~

~~capture fine-grained information such as flood area edges, texture, and pixel position distribution, while deeper features extract more abstract, coarse-grained semantic information, helping solve the final pixel-level classification problem. U-Net's structural characteristics enable it to effectively handle detailed information in low-light environments, making it particularly suitable for nighttime flood detection and other low-light image segmentation tasks~~ (Yadabendra et al., 2022).

We conducted comparative experiments on the FCN, LRASPP, U-Net, and NWseg models, evaluating their performance using metrics such as Precision, Recall, Mean Intersection over Union (MIoU), and F1 Score. All models were initialized with pretrained weights for their backbone networks and trained on the nighttime urban flooding dataset. The models were then evaluated on the test set, with relevant metrics calculated to determine the most suitable model for nighttime urban flood recognition.

3 Design of experiments

3.1 Construction of dataset

In this study, we employed web crawler technology using Google Chrome to construct a comprehensive nighttime urban waterlogging dataset by searching with the keyword "nighttime urban flooding." This dataset contains 4,000 images that capture a wide range of nighttime waterlogging scenes, varying in extent and shape. To enhance the dataset's robustness and comprehensiveness, we included images of complex scenes, such as strong lighting conditions and splashes caused by vehicles, ensuring its applicability to diverse nighttime flooding situations. During the data selection process, careful attention was given to the representativeness and balance of waterlogged areas across different scales, ranging from localized ponding to large-scale flood events, to ensure broad coverage of possible urban flooding conditions (Du et al., 2025).

In addition, we employed Labelme, an open-source image annotation tool widely used in the field of computer vision, to manually annotate the flooded regions in the images. Through its graphical interface, annotators can polygonally map the inundated areas in an image and assign corresponding category labels to each area, thus generating high-quality semantic segmentation data that can be used for deep learning model training (Zhang et al., 2023). Using this tool, we precisely labeled the inundated areas in a total of 4,000 images. To ensure the accuracy and consistency of the annotations, three graduate students with research backgrounds in urban flooding were recruited to independently perform the annotation work. Specifically, each flood image was annotated separately by all three annotators, followed by a cross-review process to identify potential discrepancies in the flood boundaries. In cases of inconsistency, the annotators engaged in multiple rounds of collaborative discussion and iterative refinement, optimizing the boundaries based on image details. This process ensured the overall quality and reliability of the dataset.~~performed the labeling work on the 4000 images in the dataset using the Labelme tool, which accurately extracted the waterlogged regions in each image. To further improve the accuracy of the annotations, we specifically assigned three graduate students to rigorously review and calibrate the boundary annotations for~~

~~quality assurance. The annotation results are saved as labeled images.~~ Figure 2 presents a comparison between the original images and the labeled images, where the inundated ~~waterlogged~~ areas are marked in white and the non-inundated ~~waterlogged~~ areas are marked in black.

Figure 2: Samples and the flood area labels in the dataset, the white marked range is the flood extent.~~Data Samples~~

3.2 Evaluation metrics

In validation and testing, mean Intersection over Union (MIoU), F1score, precision and recall were used to assess the performance of the semantic segmentation models (Munawar et al., 2021)~~(Jin et al., 2024)~~.

The MIoU value is defined as the ratio of the intersection area of the predicted bounding box and the real bounding box to the concatenation area, and is calculated by averaging the results for each category. It is used to evaluate the accuracy of the location information of the predicted results of the target detection task. The larger the overlap area between the real and the presumed area of the object, the larger the calculated value of MIoU, and the more accurate the presumed target area. The calculation of the MIoU value follows the following formula:

$$MIoU = \frac{1}{k+1}\sum_{i=0}^{k}\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \tag{1}$$

Precision, which is the proportion of samples predicted to be positive that are actually positive, is also known as the check rate, and can be expressed by the following formula:

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Recall, which is the proportion of actual positive samples that are predicted to be positive, is also known as the check all rate, and is given by the following formula:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F1_score is the reconciled mean of precision and recall. The formula for each precision evaluation metric is as follows:

$$F1score = \frac{2 \times \Pr ecison \times \mathrm{Re} call}{\Pr ecison + \mathrm{Re} call} \tag{4}$$

In the above formula, TP is the number of actual situations that are true and predicted to be true; FP is the number of actual situations that are false and predicted to be true; FN is the number of actual situations that are true and predicted to be false; and TN is the number of actual situations that are false and predicted to be false.

3.3 Experimental configuration

All experiments were conducted using an operating system of Windows 10, a CPU model of Intel(R)Core(TM)i712700F@2.10GHz, a GPU model of NVIDIA GeForce RTX 3080~~NVIDIAGeForceRTX3080~~, 32GB of operating memory,~~,~~ a programming language of Python 3.13, and a deep learning framework of PyTorch1.13, GPU acceleration is enabled during model training with CUDA 11.7 and cuDNN 8.4.1 to improve training efficiency.~~GPU acceleration libraries are CUDA11.7, CUDNN8.4.1. the~~ The input image resolution is 512*512 pixels, the training optimizer type is Adam, the weight decay index is 0.0001, and the initialized learning rate is 0.005. Parameters are shown in Table 1.

Table 1. Configuration table of the experiment

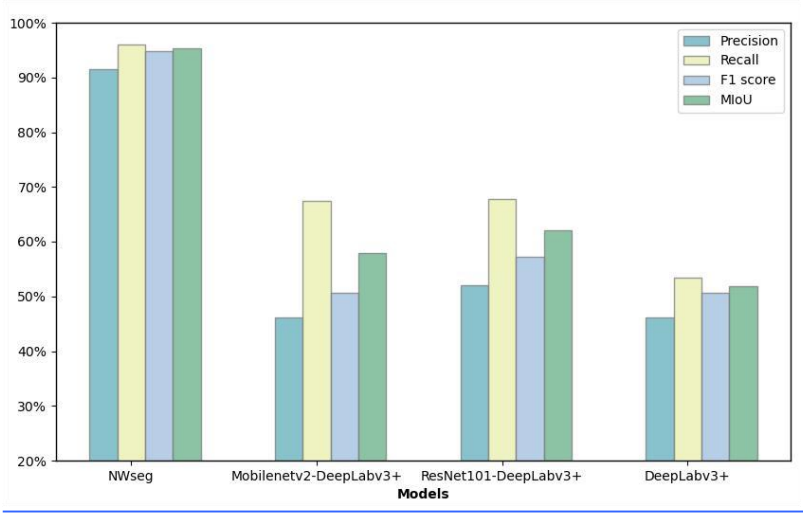
Project	Model
Operating System	Windows 10
Programming Language	Python3.13
GPU	NVIDIA GeForce RTX3080
GPU memory	32GB

4 Result

4.1 Ablation study

Table 2. NWseg and DeepLabv3+ series model training results

Models	P/%	R/%	F1_score/%	MIoU/%	Params/M
Mobilenetv2-DeepLabv3+	67.46	50.64	57.85	46.15	5.81
ResNet101-DeepLabv3+	67.74	57.24	62.05	51.98	59.34
DeepLabv3+	53.34	50.61	51.94	46.07	54.70
NWseg	95.99	94.8	95.39	91.46	122.6



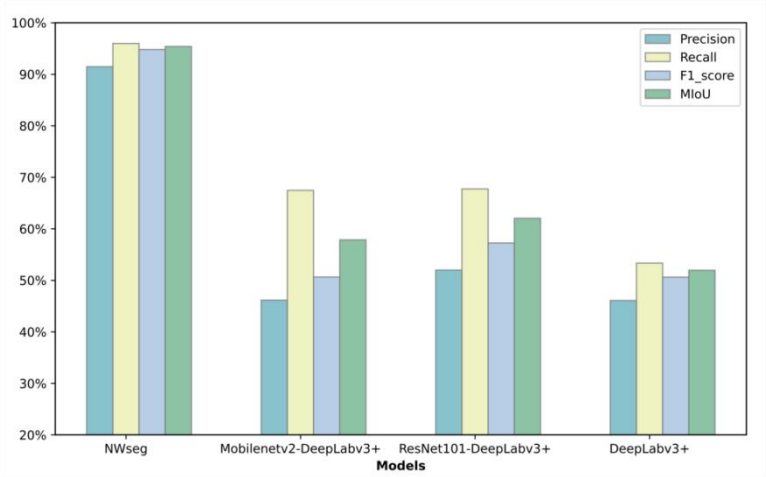


Figure 3. Comparison of experimental results between NWseg and DeepLabv3+ series of models

In this section, we present a comparative analysis of the DeepLabv3+ model with different backbone networks and compare it with the NWseg model. As shown in Table 2 and Figure 3, all evaluation metrics are improved after replacing the original backbone network of DeepLabv3+ with Mobilenetv2 and ResNet101, respectively. Notably, ~~replacing the original backbone of DeepLabV3+ with MobileNetV2 resulted in improvements across all evaluation metrics. Precision and F1score increased significantly by 14.12% and 5.91%, respectively, while Recall and MIoU saw marginal improvements of 0.03% and 0.08%.~~ ~~When~~ when ResNet101 was used as the backbone, the model's performance improved even more, with Precision, F1 score, Recall, and MIoU increasing by 14.4%, 10.11%, 6.63%, and 5.91%, respectively, compared to the baseline model. However, all DeepLabv3+ variants still exhibited a significant performance gap when compared to NWseg. The NWseg model achieved 95.99% in Precision, 94.80% in Recall, 95.39% in F1 score, and 91.46% in MIoU, demonstrating its superior capability in nighttime urban flood extent recognition. Although NWseg has a relatively large number of parameters, it delivers outstanding accuracy and robustness. ~~Despite these improvements, all three DeepLabV3+ models still exhibited a noticeable performance gap compared to the NWseg model. The NWseg model significantly outperforms the other models by achieving 95.99%, 94.8%, 95.39%, and 91.46% in Precision, Recall, F1 score, and MIoU, respectively.~~

4.2 Model performance experiments

Table 3. NWseg and other segmentation model training results

Models	P/%	R/%	F1_score/%	MIoU/%	Params/M
NWseg	95.99	94.8	95.39	91.46	122.6
ResNet50-FCN	85	77.23	80.93	82.7	35.31
LRASPP	80.17	25.39	38.57	59.21	3.22
U-Net	94.7%	83.57	88.24%	80.5%	43.93

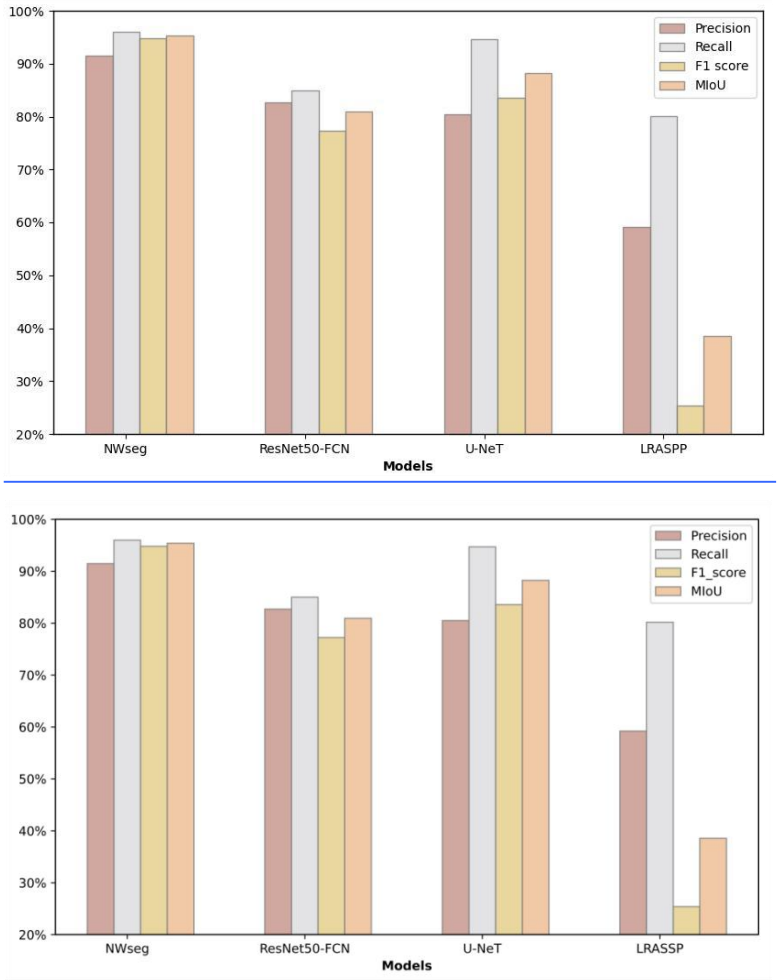


Figure 4. Comparison of experimental results between NWseg and other segmentation models

In this section, we present a comparative analysis of the experimental results of the NWseg model against other segmentation models. As shown in Table 3 and Figure 4, the NWseg model achieved optimal results on the test set of the nighttime flood inundation~~social inundation~~ dataset, with a Precision of 95.99%, Recall of 94.8%, F1-score of 95.39%, and MIoU of 91.46%. These metrics are significantly higher than those of the other models, demonstrating superior ~~exceptional~~ accuracy and recall rates. Compared to the ResNet50-FCN model, the NWseg model exhibits superior performance across all indicators, with increases of 10.99% in Precision, 17.57% in Recall, 14.46% in F1-score, and an 8.76% improvement in MIoU. When compared with the U-Net model, while the NWseg's Precision is similar, it outperforms in other metrics, with Recall, F1-score, and MIoU higher by 11.23%, 7.15%, and 10.96% respectively. Additionally, compared to the lightweight LRASPP model, the NWseg model shows more pronounced advantages, with Precision increased by 15.82%, Recall

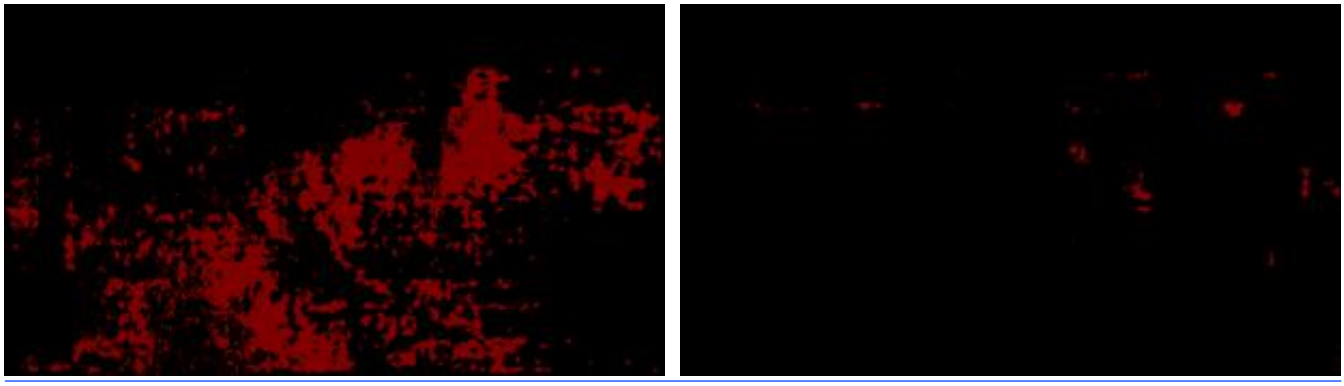
significantly increased by 69.41%, F1 -score improved by 56.82%, and MIoU enhanced by 32.25%. Although NWseg is higher in the number of model parameters than the other comparative models, it still demonstrates significant advantages in several evaluation metrics. Future research will aim to further optimize the structure of the model while maintaining its performance to achieve a higher degree of lightweighting.~~The lightweight design of LRASPP limits its ability to precisely capture details and edges, resulting in lower overall recognition accuracy.~~

Overall, the NWseg model demonstrates superior performance across all evaluation metrics and also shows strong performance in real scenario tests. In contrast, although the ResNet50-FCN model performs well in precision and detail processing, it lacks efficacy in handling edge regions, leading to slightly insufficient performance in complex scenes. While LRASPP offers advantages in computational efficiency due to its lightweight design, it has limitations in the precise capture of details and boundaries. The U-Net model is comparable to NWseg in accurately detecting target areas but is somewhat less robust and consistent when processing complex scenes.

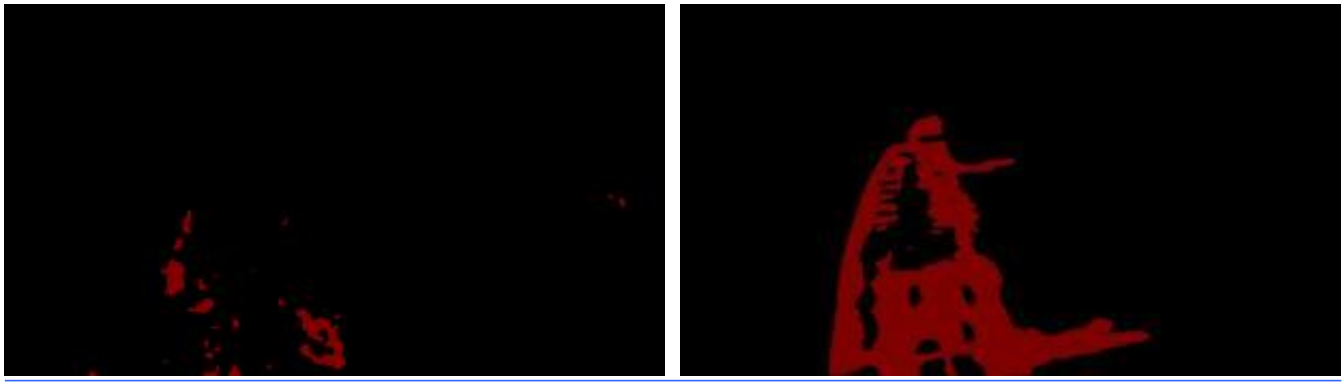
4.3 Real-world scenes prediction comparison

To validate the effectiveness and stability of each model under challenging scenes, we conducted tests on seven models using nighttime rainfall scenes and nighttime strong illumination scenes (Wan et al., 2025)~~(Liang et al., 2023)~~. As shown in Figure 5(a) presents the original scene where streetlights at night generate strong reflections and halos on the water surface. Additionally, the intense lighting affects the detailed features of the ground. By comparing the recognition results of each model, it is evident that the NWseg, ResNet50-FCN, and U-Net models accurately detected the flooding conditions in the scene. Notably, the NWseg model exhibited a more refined recognition ability in identifying water accumulation in road depressions. However, both ResNet50-FCN and U-Net showed certain false detections when recognizing the overall flooded areas. In contrast, the Mobilenetv2-DeepLabv3+, DeepLab, and LRASPP models could only sporadically identify small flooded regions and exhibited varying degrees of false detections. Although the ResNet101-DeepLabv3+ model recognized a larger flooded area, a comparison with the original image reveals a relatively high false detection rate, indicating deviations in prediction accuracy. Overall, the NWseg model outperformed the others in this scene recognition task, demonstrating superior capability in recognizing flooded areas under complex lighting conditions.

(A) The Original image (B) Segmentation of Mobilenetv2-DeepLabv3+



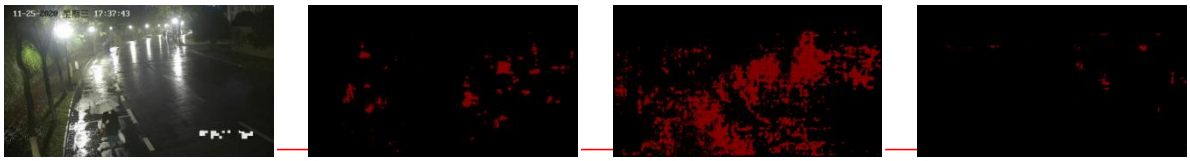
(C) Segmentation of ResNet101-DeepLabv3+ (D) Segmentation of DeepLabv3+



(E) Segmentation of LRASPP (F) Segmentation of U-Net

(G) Segmentation of ResNet50-FCN (H) Segmentation of NWseg

~~(a) Original image (b) Mobilenetv2-DeepLabv3+(c) ResNet101-DeepLabv3+ (d) Deeplab~~



~~(a) Original image (b) Mobilenetv2-DeepLabv3+ (c) ResNet101-DeepLabv3+ (d) Deeplab~~

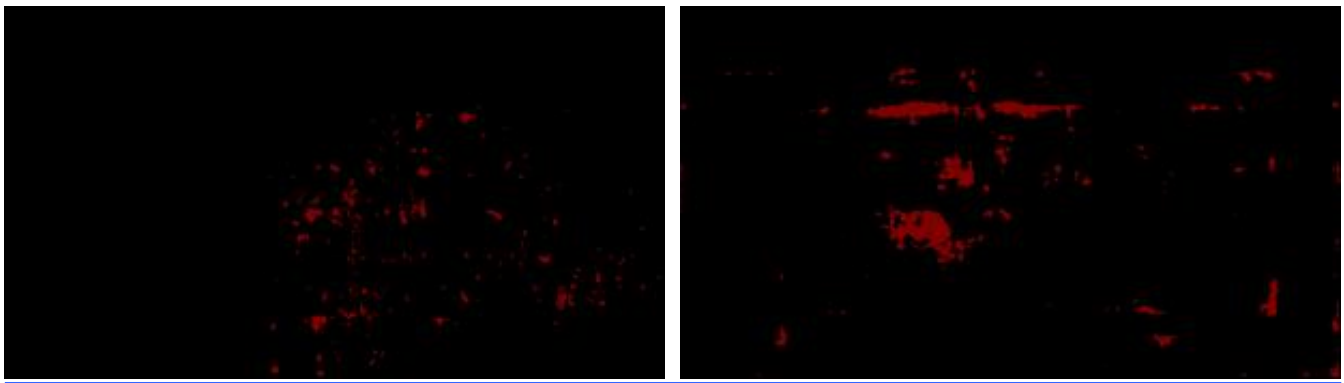
~~(e)NWseg (f) ResNet50-FCN (g) LRASPP (h) U-Net~~

Figure 5. Scene with nighttime strong illumination: (A) the original scene; (B) the segmentation result of Mobilenetv2-DeepLabv3+; (C) the segmentation result of ResNet101-DeepLabv3+; (D) the segmentation result of DeepLabv3+; (E) the segmentation result of LRASPP; (F) the segmentation result of U-Net; (G) the segmentation result of ResNet50-FCN; (H) the segmentation result of NWseg;~~Examination of nighttime strong illumination scenes~~

Furthermore, in the nighttime rainfall scene tests, we evaluated each model's performance to simulate urban flood recognition under real-world conditions ~~(Tan et al., 2021)~~. In such scenes, reflections from rainwater, slippery road surfaces, and interference from raindrops on the camera lens can adversely affect image clarity and the models' recognition accuracy (Zhao et al., 2025). As shown clearly in Figure 6, the NWseg, ResNet50-FCN, and U-Net models were able to correctly identify the flooded areas in the images, with the NWseg model providing the most detailed performance by accurately capturing the edges of the flooded regions. While ResNet50-FCN and U-Net also identified the extent of flooding relatively well, they were somewhat insufficient in recognizing the flood boundaries and exhibited some false detections.

In contrast, the other four models performed relatively poorly. Specifically, the LRASPP and Mobilenetv2-DeepLabv3+ models were almost unable to detect the flooding, indicating weaker recognition capabilities in nighttime rainfall scenes. Although ResNet101-DeepLabv3+ and DeepLab could detect some flooded areas, comparison with the original images revealed that the regions identified did not accurately reflect the actual flooding conditions and had high false detection rates. Through comparative analysis, we further confirmed the challenges posed by nighttime rainfall environments for urban flood recognition and demonstrated the superior performance of the NWseg model in handling complex conditions such as nighttime rainfall.

(A) The Original image (B) Segmentation of Mobilenetv2-DeepLabv3+



(C) Segmentation of ResNet101-DeepLabv3+ (D) Segmentation of DeepLabv3+

(E) Segmentation of LRASPP (F) Segmentation of U-Net

(G) Segmentation of ResNet50-FCN (H) Segmentation of NWseg

~~(a) Original image (b) Mobilenetv2-DeepLabv3+ (c) ResNet101-DeepLabv3+ (d) Deeplab~~

~~(e) NWseg (f) ResNet50-FCN (g) LRASPP (h) U-Net~~

Figure 6. Scene with nighttime rainfall: (A) the original scene; (B) the segmentation result of Mobilenetv2-DeepLabv3+; (C) the segmentation result of ResNet101-DeepLabv3+; (D) the segmentation result of DeepLabv3+; (E) the segmentation result of LRASPP; (F) the segmentation result of U-Net; (G) the segmentation result of ResNet50-FCN; (H) the segmentation result of NWseg;

~~**Figure 6. Examination of nighttime rainfall scenes**~~

5 Discuss

In this study, a state-of-the-art model named NWseg is proposed to address the challenges of nighttime urban flood extent identification. Through a series of experimental validations, the NWseg model demonstrates superior performance with

95.99%, 94.8%, 95.39%, and 91.46% in Precision, Recall, F1 score, and MIoU, respectively. In the prediction comparison of real scenarios, the model also shows high accuracy and robustness, and effectively recognizes flooded areas in complex nighttime environments. In addition, NWseg achieves an inference speed of 37.8 FPS (i.e., approximately 26.5 milliseconds per image) under the NVIDIA GeForce RTX 3080 environment, demonstrating its potential for real-time applications in high-performance computing platforms. This study bridges the current research gap in flood extent recognition in nighttime scenarios, providing a technical reference for flood monitoring and emergency response.

Nevertheless, this study still has some limitations. First, the overall structure of NWseg is relatively complex, and the model parameters are large in scale, which limits its deployment capability on resource-constrained edge devices. On the other hand, in nighttime scenarios with extremely low illumination or even complete power outage (e.g., the case of city blackout triggered by heavy rainfall), the model has difficulty in extracting effective edge and texture information, which leads to a significant degradation of the recognition performance. In the future, we will further optimize the network structure to reduce the computational complexity of the model and improve deployment flexibility. In addition, we consider combining infrared thermal imaging, low-light image enhancement, or multimodal fusion methods to improve the robustness and generalization ability of the model under extreme low-light conditions.

~~5~~6 Conclusions

This study successfully verified the excellent performance of the NWseg model in nighttime urban flood monitoring (Wan et al., 2024), which provides a new idea for multi-scene flood extent identification and helps to promote the flood monitoring system towards all-weather and all-scene intelligent identification.~~addresses the technical challenges of nighttime urban flood detection by evaluating the performance of seven different models (Wan et al., 2024).~~ First, we constructed a representative dataset comprising 4,000 images of nighttime urban flooding scenes, covering various nighttime environments and diverse urban backgrounds. Second, a model for nighttime waterlogging recognition, NWseg, is proposed to address the limitations in nighttime waterlogging recognition due to insufficient lighting and complex lighting conditions. Furthermore, we replaced the backbone networks of the DeepLabv3+ model with MobilenetV2 and ResNet101 and conducted ablation experiments to validate the performance of DeepLabv3+ with different backbones in nighttime flood recognition. We also performed a comparative analysis between these DeepLabv3+ models and the NWseg model, as well as systematically analyzed the NWseg, ResNet50-FCN, U-Net, and LRASPP models. Based on this, we reached the following empirical findings:

(1) Within the DeepLab series, the DeepLabv3+ model using ResNet101 as the backbone outperformed other variants in capturing water surface edges and shadow details. However, when compared to the NWseg model, there remains a considerable performance gap.

(2) The NWseg, U-Net, and ResNet50-FCN models demonstrated excellent performance in recognizing large-scale flooded areas, effectively capturing the overall contours of flood zones and exhibiting strong generalization capabilities. Specifically, NWseg shows higher accuracy and robustness in complex scene tests, while ResNet50-FCN and U-Net have some deficiencies and false detections in detecting edge details. In contrast, the lightweight LRASPP model showed limited ability to recognize flooded areas in nighttime scenes, resulting in relatively poor performance.

(3) Through examining each model in complex scenes, we validated the NWseg model's effectiveness and stability in diverse environments and conditions.

This study successfully demonstrates the superior performance of the NWseg model in nighttime urban flood detection, filling the research gap in nighttime flood range identification. Our work not only promotes the development of the field of nighttime urban flood identification but also provides a reference for future deep learning applications under extreme lighting conditions (Wan et al., 2024). However, the model's decoupling and parsing process involves complex decomposition of lighting components and adaptive fusion, leading to high computational resource demands, which may impact its practical usability. Future work will focus on reducing the model's parameters and computational costs while maintaining accuracy. Additionally, further optimization of the dataset and model improvements will be pursued to enhance the overall performance of the NWseg model, broadening its potential applications.

Acknowledgments. This research was funded by the National Natural Science Foundation of China (NSFC) (No.42405140), the China Postdoctoral Foundation (No. 2024M761383), the Open Grants of China Meteorological Administration Radar Meteorology Key Laboratory (No. 2024LRM-A02), and the Talent Startup project of NJIT (YKJ.202315).

Data availability. Data will be made available on request.

Author contributions. **Xing Wang, Jiaquan Wan, Yannian Cheng, Cuiyan Zhang**: Writing – original draft, Validation, Software, Methodology, Investigation. **Xing Wang, Jiaquan Wan, Yannian Cheng**: Writing – review & editing, Validation. **Tao Yang**: Writing – review & editing, Supervision. **Fengchang Xue:** Formal analysis, Validation. ~~**Yufang Shen:** Data curation, Validation.~~ **FT**: Data curation, Validation. **Quan J. Wang**: Data curation, Validation.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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