Intersection Flood Detection Using a Grid-Based Two-Stage Classifier

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***Abstract*— Frequent urban flooding caused by extreme weather events has emerged as a serious threat to traffic safety and infrastructure. Traditional flood detection systems, such as those based on IoT sensors or hydrological simulations, are limited by high installation costs and poor scalability. To address these issues, this study proposes an intersection flood detection system based on a grid-based two-stage classifier using CCTV images. The first stage classifier determines whether the road surface is dry or wet. The second stage classifier determines whether a road is flooded or not. To determine whether a road is normal, partially flooded, or completely flooded, the image is divided into grids and flooding is determined for each grid. This allows us to identify which grids are flooded and determine the extent of the flooding. The proposed method enables fast and reliable detection even in complex intersection environments. Experimental results demonstrate high detection accuracy and robustness against lighting and occlusion, confirming its potential for real-time deployment in smart city infrastructure.**

Keywords—Flood detection, Two-Stage Classifier, Intersection Surveillance

I. Introduction

In recent years, the frequency and intensity of heavy rainfall have increased significantly due to global climate change, leading to severe flooding in urban areas. Among these, intersections represent critical points of risk, as even minor flooding can disrupt traffic flow, damage vehicles, and endanger pedestrians. The need for a real-time, cost-efficient flood detection system that can monitor intersections continuously has become increasingly urgent.

Conventional flood monitoring approaches can be categorized into three main types: (1) Forecast-based methods that utilize meteorological and hydrological big data for flood prediction, (2) Sensor-based systems that rely on IoT water-level sensors installed near drainage points, and (3) Vision-based detection using CCTV footage. While forecast-based systems are useful for long-term planning, they lack real-time responsiveness. Sensor-based methods provide high accuracy but suffer from limited coverage and high maintenance costs. In contrast, CCTV-based flood detection leverages existing surveillance infrastructure and offers scalable deployment. However, these methods still face challenges such as illumination variation, reflections, occlusions by vehicles, and diverse intersection layouts. To overcome these limitations, this study introduces a grid-based two-stage flood detection system designed specifically for intersection environments. The system first detects whether it is raining by classifying the road surface condition and then quantifies the flooding level through fine-grained spatial analysis. This approach ensures both high accuracy and real-time operational efficiency suitable for intelligent transportation and smart city systems.

II. The Proposed System

In this paper, we propose an intersection flood detection system using a grid-based two-stage classifier. The proposed system consists of two main modules: Stage 1—Road Wetness Classification and Stage 2—Flood Level Classification. Each stage operates sequentially on CCTV video streams to achieve robust and interpretable flood detection.

The first stage aims to determine whether the road surface is dry or wet. This step acts as a filtering mechanism to minimize unnecessary processing during non-rainy conditions. The classifier is implemented using YOLOv8s, a lightweight convolutional neural network optimized for real-time applications [1]. The model was trained on a hybrid dataset combining publicly available road images and internally collected intersection footage [2]. We collected video files from 40 cameras at 10 intersections, covering a variety of time periods and weather conditions. Figure 1 shows sample images from the dataset used for wetness classifier training. 13,000 dry images and 14,000 wet images were used to train the classifier. Figure 2 shows the training results. Using 50 epochs of training, we observed that the loss converged to near 0 and the top-1 accuracy was close to 100%. Figure 3 shows the test result images of the wetness classifier in various environments. We confirmed that the model performed well on actual test images without any misclassifications. It was confirmed that the wetness of the road surface was accurately classified even in poor environments such as nighttime environments and vehicle headlight glare.

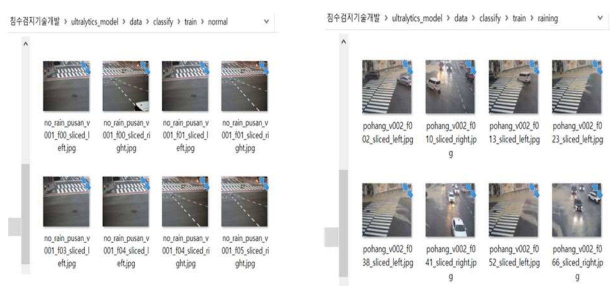

Fig. 1. Samples images of dataset for the wetness classifier training

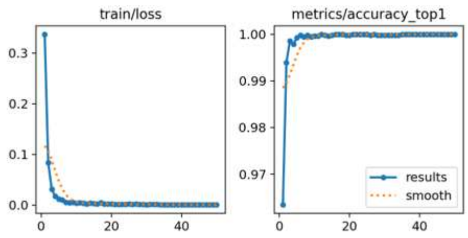

Fig. 2. Training results of wetness classifier

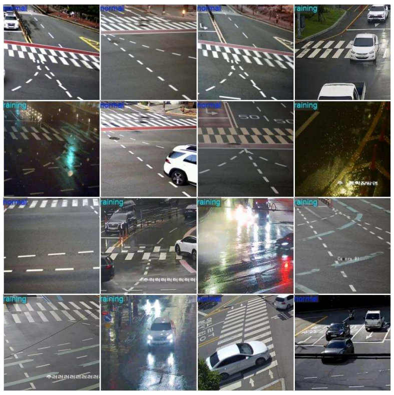

Fig. 3. Test result images of the wetness classifier

When the roadway appears wet, we assess whether it is actually flooded. To this end, the roadway is partitioned into a grid, and flood status is inferred for each grid cell. Aggregating the cell-level decisions yields the flood-level status of the roadway as normal, partially flooded, or fully flooded. We first develop a binary classifier to determine whether a visually "wet" roadway corresponds to an actual flood condition. The classifier operates on image frames extracted from intersection CCTV streams and returns a flood/non-flood decision for each input. To train the classifier, we curated a balanced dataset using flood videos and publicly available open databases. Specifically, we compiled approximately 5,000 positive images (flood) and 5,000 negative images (non-flood). Fig. 4 presents representative samples from the constructed training database. The flood classification model adopts YOLOv8s as the backbone. YOLOv8s is a lightweight, real-time object detection model that balances speed and accuracy via an anchor-free head and optimized backbone, making it suitable for edge or latency-sensitive deployments. Training was conducted on the above dataset, and the learning dynamics are summarized in Fig. 5, which reports the evolution of training loss and accuracy over epochs. he trained classifier achieves an accuracy of approximately 95% on the evaluation set. Qualitative results are illustrated in Fig. 6, demonstrating that the model maintains reliable performance across diverse environmental conditions (e.g., illumination changes, glare, reflections, and varied viewpoints). Even under adverse scenes, the classifier consistently distinguishes flood from non-flood instances.

Fig. 4. Samples images of dataset for the wetness classifier training

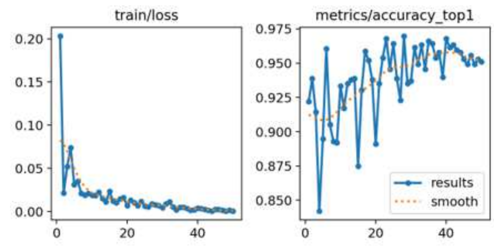

Fig. 5. Training results of flood classifier

Fig. 6. Test result images of the flood classifier

An initial approach using crosswalk line detection was investigated, where the visibility of white rectangles gradually decreased with rising water. However, this approach proved unreliable in intersections lacking crosswalks or where occlusion by vehicles occurred [3]. To enhance general applicability, a grid-based detection approach was developed. The video frame is divided into an eight-cell grid (2×4), and each region is independently analyzed to determine whether flooding is present. Detection is based on changes in color intensity, reflection patterns, and local contrast features. By aggregating these regional decisions, the overall flooding level is computed as follows.

TABLE 1. FLOOD STATUS AGGREGATION TABLE

Number of Flooded Regions (out of 8)	Flood-level Status
0	Normal
1-4	Partial Flood (Caution)
5-6	Partial Flood (Severe)
7-8	Full Flood (Alert)

Empirically, the drivable roadway occupies the lower two-thirds of intersection CCTV frames. We therefore define a fixed ROI R as the bottom 2/3 of each frame and run all subsequent analysis within R. This choice concentrates computation on road pixels while being robust to modest camera pose changes. The Stage-1 wetness classifier processes only R to decide *dry* vs. *wet*. If *dry*, the pipeline idles without invoking further modules. When R is judged *wet*, R is partitioned into eight tiles (a 2×4 grid). The flood classifier produces a binary *flood / non-flood* label for each tile. Two operating modes are supported: auto-grid, which uniformly tiles R; and operator-defined ROI, where users specify persistent regions-of-interest per camera to better align tiles with lanes, crosswalks, or drainage areas. Figure 7 illustrates the automatically generated 2×4 grid over the roadway region used for cell-level classification. Figure 8 presents an example from real flood footage: the Stage-1 module classifies the roadway surface in the lower two-thirds as wet, after which each grid cell is evaluated by the Stage-2 classifier to produce flood / non-flood labels.

Fig. 7. Automatically configured 2×4 grid over the bottom two-thirds ROI for cell-level inference

Fig. 8. Qualitative result on real flood footage: wetness classification of the roadway (Stage 1) followed by per-cell flood classification (Stage 2) across the **2×4** grid.

Because flood progression does not require millisecond latency, the pipeline employs adaptive sampling. Initially, frames are analyzed at a relaxed interval. Upon detecting any flooded tile, the interval is reduced to track the event more closely. This strategy reduces redundant inference while preserving timely detection during onset and escalation.

To support practical deployment of the proposed flood - detection algorithm, we implemented a web-based monitoring system. The system comprises (i) map-centric visualization of CCTV nodes at intersections, (ii) real-time presentation of status levels—normal, caution, danger, and alert—and (iii) drill-down navigation to a detailed view via icon selection. In the detailed view, operators can access the live video stream; when the detector raises a flood event, the system automatically generates and archives the corresponding event clip for immediate review, thereby facilitating timely on-site decision-making.

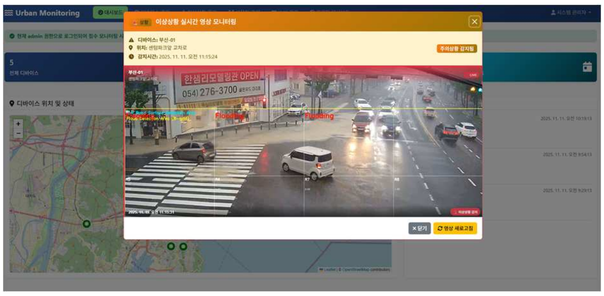

Fig. 9. Web-based flood monitoring system

III. Conclusion and Future Work

This paper presented a two-stage classifier-based intersection flood detection system utilizing CCTV footage. The proposed system effectively integrates road wetness detection and flood-level classification to provide accurate, interpretable, and real-time flood assessment in urban environments. Experimental results confirmed that the system performs robustly under diverse lighting and weather conditions, maintaining high detection accuracy even with occlusions. The grid-based spatial classification method allows detailed and scalable flood assessment across intersections.

Future research will focus on integrating flood depth estimation using geometric modeling and multi-camera fusion for broader spatial coverage. Additionally, the system can be connected to real-time alert and control infrastructures, contributing to intelligent transportation systems and smart city disaster management frameworks. Ultimately, the proposed method demonstrates a practical and scalable approach toward enhancing urban flood resilience through AI-based video analysis.

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