

Single-Camera Flood Monitoring Using YOLOv5 for Water Level and Turbidity Detection

Gamma Aditya Rahardi¹, Sherly Apta Maharani², Hasanur Mohammad Firdausi³,
Satryo Budi Utomo⁴, Dani Hari Tunggal Prasetyo⁵

^{1,2,4} Department of Electrical Engineering, University of Jember, Jember 68121, East Java, Indonesia

³ Department of Informatics, KH Bahaudin Mudhary Madura University, Sumenep 69451, East Java, Indonesia

⁵ Department of Mechanical Engineering, University of Jember, Jember 68121, East Java, Indonesia

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ABSTRACT

Floods are one of the most common natural disasters and require efficient early warning systems to mitigate their effects on infrastructure and communities. Conventional flood monitoring systems generally consist of many physical sensors, which may incur higher maintenance cost and reduce the system robustness in a severe river environment. The purpose of this study is to create a single-camera flood monitoring system that is capable of detecting water level and water turbidity in real-time using YOLOv5. An initial dataset containing 1,711 original images was collected and augmented to 4,104 images for model training and evaluation. Four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) were trained for 50 and 150 epochs. Experimental results show that all models have high detection performance with precision, recall and mAP values above 0.98. YOLOv5s achieved the best real-time performance with 4.26 FPS and maintained competitive accuracy. Detection failures due to overexposure were observed at high illumination levels and illumination analysis indicated that detection can be reliably performed under lighting conditions below 25,000 lux. The proposed system provides a vision-based alternative for real-time inundation early warning applications.



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Corresponding Author:

Gamma Aditya Rahardi

Department of Electrical Engineering, University of Jember, Jember 68121, East Java, Indonesia

Email: gamma.rahardi@unej.ac.id

1. INTRODUCTION

Floods are among the most destructive natural disasters worldwide, causing significant losses of human life, economic activities, and infrastructure. In Indonesia, floods frequently occur due to rapid urbanization, high-intensity rainfall, land-use changes, and inadequate drainage systems. They are commonly characterized by rising water levels, increased sediment transport, debris movement, and higher water turbidity, which serve as important indicators of flood occurrence and severity. Recent studies have highlighted the growing need for advanced flood monitoring and forecasting systems to improve disaster preparedness and mitigation [1] - [3].

Timely information is essential for effective flood Early Warning Systems (EWS). Modern EWS increasingly integrate artificial intelligence, hydrological modeling, and real-time sensing technologies to improve prediction accuracy and response capability [4] - [6]. However, developing a reliable and scalable monitoring system remains challenging, particularly in river environments where sensor

installation and maintenance are difficult. Therefore, continuous monitoring approaches capable of operating under varying environmental conditions are highly desirable [1], [7].

Various methods have been proposed for flood monitoring. Ultrasonic sensors are widely used for water level measurement because of their simplicity and low cost [8], while turbidity sensors monitor suspended particles and water quality changes associated with flood events [9] - [11]. IoT technologies further support environmental monitoring through automatic warning dissemination, cloud data transmission, and remote monitoring [12] - [14]. More recently, deep learning and computer vision have enabled camera-based flood monitoring, including water level estimation using single-camera systems [15] - [20] and flood detection or inundation segmentation from images [21] - [23].

Despite these advances, existing flood monitoring systems still face several limitations. Many studies focus on a single flood indicator, such as water level, flood extent, or water quality [7], [22], [23]. Sensor-based approaches require multiple devices, increasing installation complexity and maintenance while remaining vulnerable to debris, sedimentation, and extreme weather [8], [10], [11]. Some systems also demand substantial computational resources or cannot operate in real-time [4], [5], [24], whereas camera-based methods are sensitive to illumination and adverse weather conditions [20]. Furthermore, only a few studies have investigated simultaneous detection of water level and water turbidity using a single-camera, and comparative evaluations of different YOLOv5 variants under varying environmental conditions remain limited [1], [3], [7], [17].

To address these limitations, this study proposes a single-camera flood monitoring system based on the YOLOv5 object detection algorithm for simultaneous water level and water turbidity detection. Four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) are evaluated under different training configurations. YOLOv5 was selected because of its strong performance in lightweight and real-time object detection applications [25] - [27]. Ultrasonic and turbidity sensors are used as reference measurements to validate the proposed vision-based system.

The main contributions of this study are: (1) developing a single-camera flood monitoring framework; (2) enabling simultaneous detection of water level and water turbidity; (3) comparing multiple YOLOv5 variants for real-time monitoring; and (4) analyzing the effect of illumination on detection performance. The proposed approach provides a vision-based alternative for real-time flood monitoring and early warning applications in river environments, complementing recent advances in computer vision-based hydrological monitoring and flood management systems [1], [2], [6], [12].

2. RESEARCH METHOD

2.1 System Architecture

The proposed flood monitoring system employs a single-camera vision-based framework integrated with reference sensors for system validation, as illustrated in Figure 1. A webcam continuously captures river images, which are processed by a laptop running the YOLOv5 object detection model to determine water turbidity and water level conditions in real-time. Camera-based monitoring has gained increasing attention because of its non-contact measurement capability and suitability for flood monitoring applications [1], [15], [17] - [19].

An ultrasonic sensor and a turbidity sensor are used as references to measure water level and turbidity (NTU), respectively. YOLOv5 predictions are compared with the sensor measurements to evaluate detection accuracy and system reliability. This hybrid approach enables validation of the vision-based system while reducing reliance on physical sensors in practical flood monitoring applications [8], [9], [12]. Similar integrations of computer vision and sensor-based systems have been reported to improve the reliability of environmental monitoring applications [2], [11].

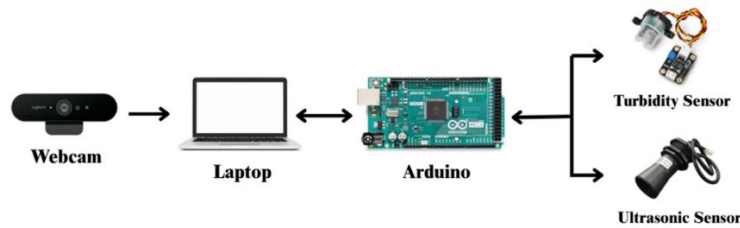


Figure 1. Overall architecture of the proposed flood monitoring system

2.2 Dataset Preparation

The dataset consisted of 1,711 original images captured under various environmental conditions, representing different water turbidity and water level scenarios. Data augmentation was applied to improve model generalization and reduce overfitting, resulting in a total of 4,104 images. Dataset diversity enhances the robustness of deep learning models under varying environmental conditions, including illumination changes and water appearance [21] - [23]. The augmented dataset was divided into training, validation, and testing sets with a ratio of 88:8:4. The training set was used for model optimization, while the validation and testing sets were used to evaluate model performance and generalization capability. Similar dataset partitioning strategies have been widely adopted in computer vision studies for flood monitoring and object detection [16], [20], [22].

Table 1. Dataset distribution

Dataset	Images
Training	3591
Validation	343
Testing	170
Total	4104

2.3 Data Annotation and Augmentation

Image annotation and dataset management were performed using the Roboflow platform. Each image was manually annotated with predefined classes representing water turbidity and water level conditions, while bounding boxes were generated for object localization during YOLOv5 training. Accurate annotation is essential for improving object localization and classification in deep learning-based monitoring systems [22], [27]. To improve model robustness and generalization, data augmentation techniques including horizontal flipping, image rotation, and blur transformation were applied. These augmentations simulate variations in camera viewpoints and illumination commonly encountered in river environments. Data augmentation has been shown to improve the generalization capability and detection accuracy of deep learning models for environmental monitoring applications [21], [25], [26].

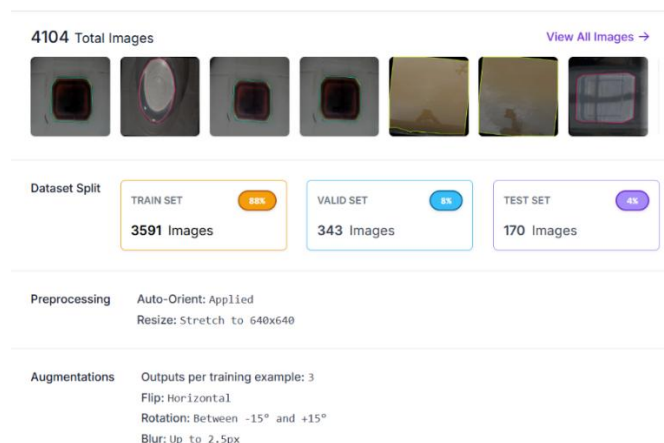


Figure 2. Dataset annotation and augmentation using Roboflow

2.4 YOLOv5 Training

This study evaluated four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) to analyze the trade-off between detection accuracy and computational efficiency. Although newer object detection models have recently been introduced, YOLOv5 was selected because of its balanced accuracy, computational efficiency, and maturity for real-time vision-based monitoring applications [13], [25] - [27]. Model training was conducted on the Google Colab and Kaggle cloud platforms using two training settings (50 and 150 epochs). The trained models were evaluated using standard object detection metrics and processing speed (FPS). Real-time inference and FPS evaluation were performed on a Lenovo ThinkPad T470 laptop equipped with an Intel Core i7-6600U processor, 16 GB RAM, Intel HD Graphics 520, and connected to a Logitech BRIO 4K webcam.

2.5 Water Level Detection Strategy

Water level monitoring was implemented using a Region of Interest (ROI)-based approach, in which the monitoring area was divided into three warning zones: Normal, Alert, and Danger. The ROI boundaries were established through an initial calibration after the camera was installed at a fixed position, using ultrasonic sensor measurements to align the corresponding waterline positions in the captured images. Thus, the system classifies the detected water level based on calibrated ROI boundaries rather than performing continuous pixel-to-centimeter conversion. Methods based on ROI are widely used for image-based water level estimation because of their simplicity and effectiveness [15], [17], [18]. Water levels below 370 cm were classified as Normal, levels between 370 cm and 610 cm as Alert, and levels above 610 cm as Danger, providing actionable information for flood early warning applications [4], [6], [8]. Since the calibration assumes a fixed camera position, significant camera displacement would require recalibration of the ROI boundaries.



Figure 3. ROI-based water level monitoring strategy

2.6 Performance Evaluation

The proposed system was evaluated using standard object detection metrics, including Precision, Recall, mean Average Precision at an Intersection over Union (IoU) threshold of 0.5 (mAP@0.5), and mean Average Precision over IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95). These metrics are widely used to evaluate deep learning models for flood monitoring and computer vision applications [7], [21], [22]. Precision measures the proportion of correctly detected objects, while Recall measures the ability to detect all relevant objects. The mAP metrics evaluate the overall localization and classification performance and have been widely adopted for flood detection and water level estimation systems [17], [18], [23]. Real-time performance was evaluated using Frames Per Second (FPS), which indicates the number of images processed per second. Higher FPS values indicate greater suitability for real-time flood monitoring applications [1], [5], [27]. The evaluation metrics are defined as:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (3)$$

where (TP), (FP), and (FN) represent true positive, false positive, and false negative detections, respectively, while (N) denotes the number of object classes.

3. RESULTS AND DISCUSSION

3.1 Sensor Calibration

The turbidity sensor was calibrated using three reference turbidity levels (10, 100, and 500 NTU) before system validation, as shown in Figure 4. The sensor exhibited different measurement errors across the turbidity range. The highest error occurred at 10 NTU (22.28%), indicating lower sensitivity to small changes in water clarity, whereas the errors at 100 NTU and 500 NTU were 1.49% and 5.33%, respectively, demonstrating better performance at medium and high turbidity levels. The calibration curve showed an inverse linear relationship between turbidity and sensor output (ADC value), expressed as:

$$y = -0.2625x + 856.04 \quad (4)$$

where x represents turbidity (NTU) and y is the ADC value. The coefficient of determination ($R^2 = 0.8285$) indicates a good correlation between the reference turbidity values and the sensor readings, demonstrating that the regression model is suitable for converting ADC values into turbidity measurements.

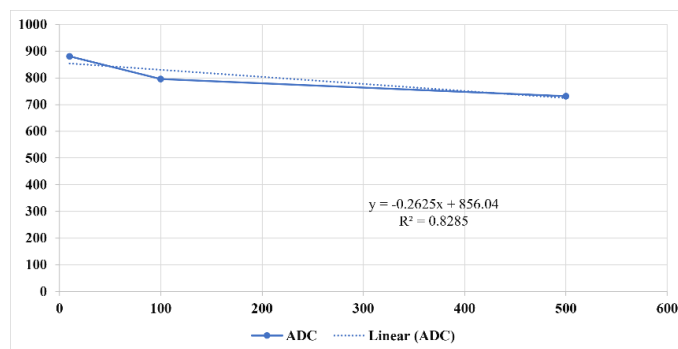


Figure 4. Turbidity sensor calibration curve

3.2 YOLOv5 Performance Comparison

The four YOLOv5 variants (YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x) were evaluated using two training settings (50 and 150 epochs), and the results are summarized in Table 2. All models achieved excellent detection performance, with precision, recall, and mAP@0.5 values above 0.99. Increasing the training from 50 to 150 epochs resulted in comparable performance across all variants, with slight improvements in mAP@0.5 for YOLOv5m, YOLOv5l, and YOLOv5x, while YOLOv5s maintained similar performance. Overall, the performance differences among the four variants were small, indicating that all models were capable of accurately detecting the water turbidity classes. Although YOLOv5m achieved marginally higher overall accuracy, YOLOv5s was selected for deployment because of its superior real-time processing speed.

Table 2. Best model performance

Model	Epoch	Precision	Recall	mAP@0.5
YOLOv5s	50	0.994	0.996	0.991
	150	0.992	0.997	0.991
YOLOv5m	50	0.995	0.997	0.990
	150	0.994	0.997	0.991
YOLOv5l	50	0.995	0.997	0.990
	150	0.994	0.997	0.991
YOLOv5x	50	0.995	0.997	0.990
	150	0.994	0.997	0.992

3.3 Loss Analysis

The training loss curves for object loss, classification loss, and box loss are shown in Figure 5. All YOLOv5 variants exhibited a rapid loss reduction during the first 20 epochs, followed by gradual convergence to stable values. YOLOv5s showed slightly larger fluctuations during the early training stage, whereas YOLOv5m, YOLOv5l, and YOLOv5x converged more smoothly. Stable box loss and decreasing object and classification losses indicate improved object localization, successful class learning, and no significant overfitting.

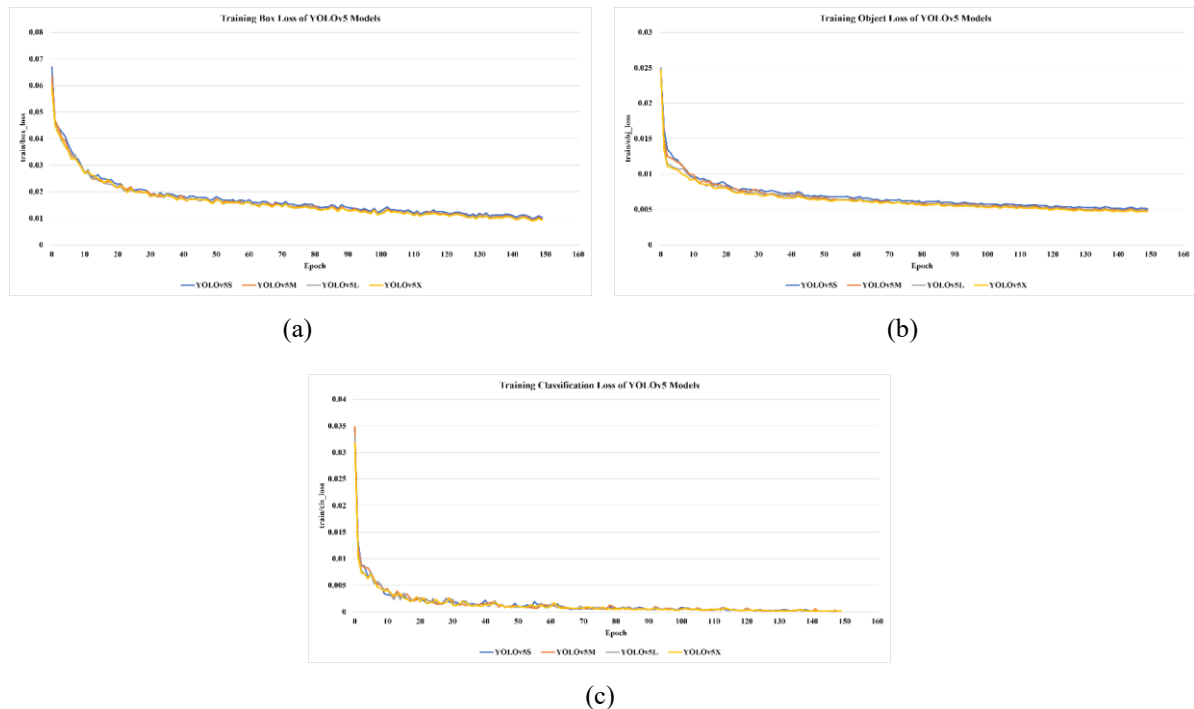
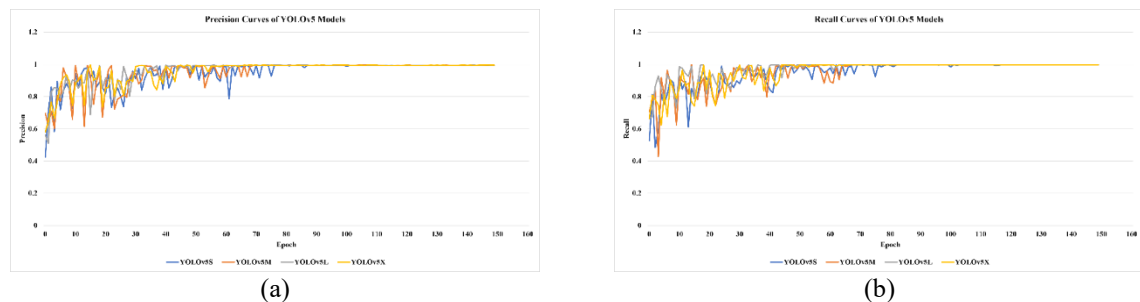


Figure 5. a. Training box loss; b. Training object loss; c. Training classification loss of YOLOv5 models

3.4 Detection Performance

Figure 6 shows the changes of precision, recall, mAP@0.5 and mAP@0.5:0.95 during training. At the beginning of the learning process, all models showed fluctuations due to parameter adaptation. After 20-30 epochs the metrics were stabilized and optimal values were obtained. YOLOv5x and YOLOv5l, on the other hand, had more stable learning behavior and faster convergence, while YOLOv5s required more epochs to reach a similar performance level. At the end of the training process, all models obtained values for precision and recall close to 1.0, indicating their high efficiency in object detection. The mAP@0.5 and mAP@0.5:0.95 demonstrated good localization and classification ability and always exceeded 0.95. The stable metric curves suggest that the trained models generalized well to unseen data.



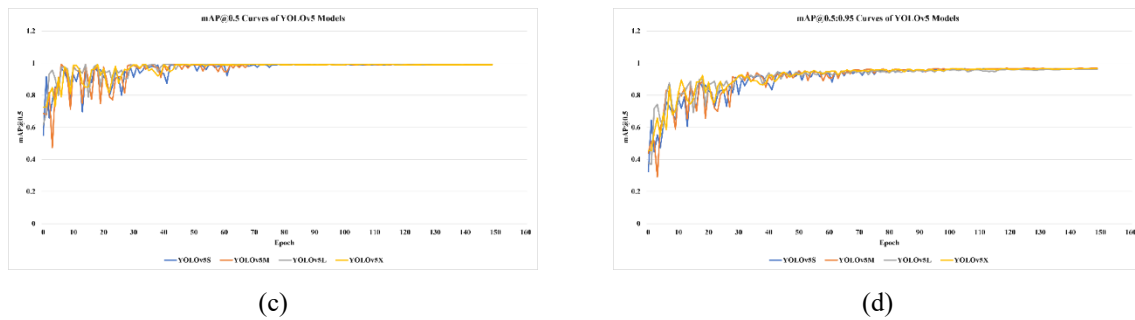


Figure 6. a. Precision curves; b. Recall curves; c. mAP@0.5 curves; d. mAP@0.5:0.95 curves of YOLOv5 models

3.5 Real-Time Performance

Frames Per Second (FPS) was used to evaluate the real-time performance of the proposed system, and the results are summarized in Table 3. A clear trade-off was observed between computational efficiency and detection accuracy. Larger models (YOLOv5l and YOLOv5x) achieved stable detection performance but at substantially lower processing speeds, whereas YOLOv5s achieved the highest speed of 4.26 FPS while maintaining competitive detection accuracy. The FPS measurements were obtained using a Lenovo ThinkPad T470 laptop equipped with an Intel Core i7-6600U processor, 16 GB RAM, Intel HD Graphics 520, and a Logitech BRIO 4K webcam. Although 4.26 FPS is lower than conventional video frame rates, it is sufficient for river flood monitoring because water level and turbidity change gradually rather than instantaneously. Therefore, YOLOv5s was selected as the most suitable model for real-time deployment of the proposed flood monitoring system.

Table 3. Real-time performance of YOLOv5 models.

Model	FPS
YOLOv5s	4.26
YOLOv5m	2.83
YOLOv5l	1.73
YOLOv5x	0.49

3.6 Illumination Analysis

The effect of the illumination on the detection efficiency was studied for different illumination conditions. The experimental results are summarized in Table 4. Detection failures were observed under extreme brightness conditions exceeding 25,000 lux. The webcam could not detect turbidity and water level at illumination levels of 39,400 lux and 87,040 lux due to overexposure and water surface reflection. On the other hand, the detections were effectively obtained under moderate and low illumination conditions below 25,000 lux, respectively. The model could detect the flood parameters accurately even with very low illumination (41 lux). Another contribution of this work is the results showing that illumination greatly affects vision-based flood monitoring systems. The findings suggest that illumination intensity is a critical factor affecting camera-based flood monitoring systems. Excessive brightness can lead to overexposure and reflection artifacts, reducing detection reliability.

Table 4. Illumination testing results.

No.	Light Intensity (Lux)	Sensor Testing		YOLO Testing		Success / Failure
		Water Turbidity (NTU)	Height (cm)	Turbidity (NTU)	Height Level	
1.	3940 x 10	216,99	206	-	-	Not Detected
2.	8704 x 10	236,04	206	-	-	Not Detected
3.	2394 x 10	243,66	203	26 – 250	Normal	Success Detected
4.	1795	247,47	202	26 - 250	Normal	Success Detected
5	41	239,85	202	26 - 250	Normal	Success Detected

3.7 Overall System Validation

The proposed vision-based system was validated by comparing YOLOv5 predictions with turbidity and ultrasonic sensor measurements. Measurements performed during field experiments showed that water turbidity values ranged between 216.99 NTU and 247.47 NTU, and water levels were between 202 cm and 206 cm. The YOLOv5 model correctly classified the water level into the Normal Region of Interest (ROI) and accurately predicted water turbidity within the 26–250 NTU category. The good agreement between the YOLOv5 predictions and the reference sensor measurements demonstrates the reliability of the proposed vision-based approach. Furthermore, the field validation confirms that the single-camera system can simultaneously monitor water turbidity and water level in real-time with results consistent with the reference sensors. These findings demonstrate the feasibility of using a single-camera vision-based approach for real-time flood monitoring and early warning applications.

4. CONCLUSION

In this work, a real-time single-camera flood monitoring system based on YOLOv5 is proposed to simultaneously detect water turbidity and water level. The experimental results demonstrate the effectiveness of the proposed vision-based approach for multi-parameter flood monitoring, with YOLOv5s identified as the most suitable model for real-time deployment due to its processing speed of 4.26 FPS while maintaining precision, recall, and mAP values generally above 0.98. Validation using turbidity and ultrasonic sensors showed good agreement between the YOLOv5 predictions and the reference sensor measurements, demonstrating the reliability of the proposed approach. In addition, illumination experiments indicated that the system operated reliably under lighting conditions below 25,000 lux, whereas detection performance degraded under severe overexposure. Overall, the proposed system demonstrates the feasibility of using a single-camera vision-based approach for simultaneous water level and turbidity monitoring to support real-time flood monitoring and early warning applications. Despite these promising results, the study was limited by reduced robustness under high illumination conditions and validation at a single river location. Future work will focus on evaluating the system in multiple river environments, improving robustness under challenging lighting conditions, and integrating the proposed approach with IoT-based early warning systems for practical flood monitoring applications.

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