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A Deep Neural Network (DNN)-Based Waterlogging Detection on Road

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Abstract

Waterlogging on roads severely impacts transportation safety majorly due to inadequate drainage systems, blocked drainage channels, poor road design and construction, especially in areas with limited or no regular monitoring and maintenance, leading to increased accidents and traffic disruptions. Identifying waterlogging from the field photographic image is challenging due to poor illumination, reflective distortions, transparent surfaces, and low resolution. This study aims to identify waterlogging on rural roads using a deep learning-based semantic segmentation approach. The YOLOv11 model was trained and tested on CDAC PARAM Siddhi-AI High Performance Computing (HPC) platform. A dataset of 1000 photographic images from the PMGSY (*Pradhan Mantri Gram Sadak Yojana*) were sourced and annotated for this purpose. The model effectiveness was evaluated using key evaluation metrics including precision, recall, F1-score, accuracy, and Intersection-over-Union (IoU). The Deep Neural Network (DNN) model achieved a precision of 91.27%, recall of 85.95%, F1-score of 87.58%, accuracy of 96.20%, and IoU of 80.06%. The results show that training DNN model on a GPU-accelerated HPC platform significantly improves both accuracy and processing speed, which is suitable approach for waterlogging detection effectively. The output model can be utilized for deployment in national programmes such as the PMGSY National GIS, offering a rapid, cost-efficient, and scalable solution for waterlogging detection on road.

1. Introduction

Waterlogging on roads is an increasingly significant issue in both urban and rural areas, severely impacting transportation systems, road infrastructure, and everyday activities. Inadequate drainage and uneven road infrastructure are common problems. Addressing this challenge requires accurate detection and mitigation strategies, calling for innovative approaches powered by deep learning and computer vision.

Rural and semi-urban areas often lack regular waterlogging monitoring infrastructure. Zhu et al. (2024) proposed a three-stage approach involving low-light image enhancement, complex visual segmentation, and Faster R-CNN with attention mechanisms for detecting tunnel waterlogging. Urban areas experience acute vulnerability due to impermeable surfaces and dense infrastructure. Lo et al. (2021) tackled this with a DNN-based approach and Internet of Video Things / Internet of Cameras (IoVT / IoC) systems enabling real-time flood monitoring to achieve waterlogging detection. Similarly, Xiong et al. (2024) addressed the challenges of detecting waterlogging under low-visibility nighttime conditions by integrating semantic segmentation and low-light image enhancement. It improves nighttime prediction accuracy. To enhance robustness, Song et al. (2024) integrated Segment Anything Model (SAM) with Large-Small Model (LSM) Co-adapter for adaptive segmentation on the UW-Bench dataset, effectively handling reflection, shallow water, and poor textures.

These studies offer a range of solutions, from sensor-free prediction methods to advanced deep learning-based detection methods, highlighting the technologies being enhanced to address waterlogging issues in various regions. This paper presents a robust deep learning and HPC-based approach for detecting waterlogging on road, with a particular focus on rural areas of India.

2. Literature Survey

The literature survey with limited available resources on waterlogging detection methods is based on insights from research publications. Several recent studies have explored deep learning and vision-based models for detecting waterlogging. Lo et al. (2021) suggested a scalable deep sensing system integrating Convolutional Neural Networks (CNNs) with the IoVT/IoC to monitor flood events in real-time. The system could process input from 2,379 cameras, effectively detecting waterlogged areas at a national scale. However, challenges such as light sensor coverage and limited visibility in urban areas remain unsolved.

To address the complexities of night-time conditions, Xiong et al. (2024) developed a semantic segmentation model. Their model improved segmentation accuracy under poor lighting by 1.7% mIoU compared to baseline models, addressing issues related to reflection and visibility in night-time scenarios. Moreover, Starke et al. (2022) addressed this by applying a lightweight YOLOv5 model to detect waterlogged patches on gravel roads using images captured from moving vehicles, showing moderate improvements.

Traditional civil engineering approaches remain valuable in waterlogging studies, especially where advanced technologies are inaccessible. Zheyu Z et al. (2013) analysed urban waterlogging in China, highlighting poor drainage and infrastructure faults, and suggested using permeable asphalt and redesigning green belts to enhance water management. Similarly, He et al. (2021) proposed an infrastructure-embedded model using smart lamp poles to monitor road water depth. This system integrated pressure sensors and camera-based vision analysis to calculate maximum waterlogging depth and issue real-time warnings. However, its accuracy was affected due to installation and placement faults of the sensors, particularly in densely populated street scenarios.

With the rise of smart cities and real-time monitoring needs, IoT-based systems have gained traction. Islam et al. (2024) presented an IoT-based waterlogging detection solution for Dhaka's drainage system, which monitors water levels, gas build-up, and flow rates in real-time using embedded sensors. However, challenges such as network reliability, power supply, and environmental sensor degradation affect long-term deployment in densely populated areas.

The reviewed papers collectively explain the development of waterlogging detection from traditional infrastructure analysis to modern AI-driven and IoT-integrated systems. Each methodology offers distinct advantages to specific environments such as urban or rural. However, they also highlight challenges such as low-visibility conditions particularly at night, increases difficulties for visual models due to poor lighting and surface reflections (Xiong et al., 2024). There are rural waterlogging detection challenges such as Starke et al. (2022) highlights key issues include the visual complexity of gravel roads, inconsistent lighting, and limited visibility from vehicle-mounted cameras. Thus, the studies highlight the multifaceted nature of waterlogging detection challenges.

3. Challenges

Waterlogging detection in rural areas of India has numerous challenges, primarily due to the scarcity of relevant datasets and the extensive computational resources needed for training deep learning models. Additional difficulties consist of low visibility, inconsistent lighting conditions, reflections from water surfaces, and the complexity of distinguishing waterlogged areas from small potholes with water.

In order to solve road safety problems in rural areas, waterlogging identification must be accomplished with accuracy and precision. At the core of these detection systems are deep learning algorithms, which play a critical role in identifying such objects. Hence, the choice of algorithm holds considerable importance. Numerous deep learning algorithms contribute to waterlogging detection, including approaches such as object detection, segmentation, transfer learning, and others.

4. Dataset

A dataset of 1000 images of waterlogged road from PMGSY citizen mobile application is used and annotated in the format suitable for model and split into the ratio 7:2:1 for training, testing and validation respectively. Originally developed for PMGSY programme, images submitted through the citizen mobile application can be viewed via the Geospatial Rural Road Information System (GRRIS), a publicly accessible Web GIS platform available at https://www.pmgsy-grris.nic.in. The waterlogging image dataset details are provided in Table 1 and the waterlogging image samples are shown in Figure 1.

Data Split Overview		
Training	**Validation**	**Testing**
700	100	200

Table 1. Waterlogging image dataset (Source: PMGSY)

Figure 1. Waterlogging dataset samples (Source: PMGSY)

To generate training and validation data, labelled images are essential. The Labelme tool is employed for annotations, and annotated images serve as inputs for training model.

5. Methodology

The proposed study focuses on waterlogging detection using YOLOv11 deep learning model. It employs transfer learning (Khanam and Hussain et al., 2024), enabling the use of pre-trained models adapted specifically to identify waterlogged areas effectively.

5.1 Data Preparation

Polygon-based waterlogging annotations were created for each image. The corresponding labels were saved in .txt files, with each annotation line following the format: (class-id, x1 y1, x2 y2, ..., xn yn). The class-id denotes the object class, while the coordinate pairs (x1 y1, x2 y2, ..., xn yn) represent the normalized positions of the polygon points, with values ranging between 0 and 1.

5.2 Training DNN Model

The model was executed on CDAC PARAM Siddhi-AI HPC Clusters within a Python environment. The identical training hyper-parameters were applied to DNN models.

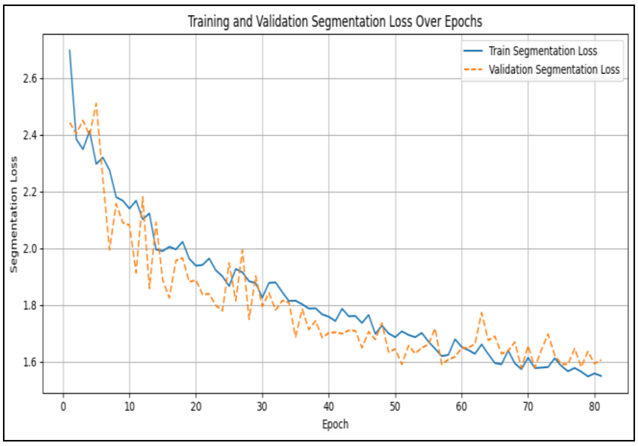

Figure 2. Training and validation loss over epochs

The model was trained using early stopping of 15 epochs. The best-performing model was obtained at the 66th epoch, after which no further improvement was observed for the subsequent 15 epochs.

The graph (Figure 2) illustrates the training and validation segmentation loss across multiple epochs. A consistent decrease in both losses over time indicates that the model is learning efficiently. Furthermore, the close alignment between validation and training loss indicates that over-fitting or under-fitting is not occurring.

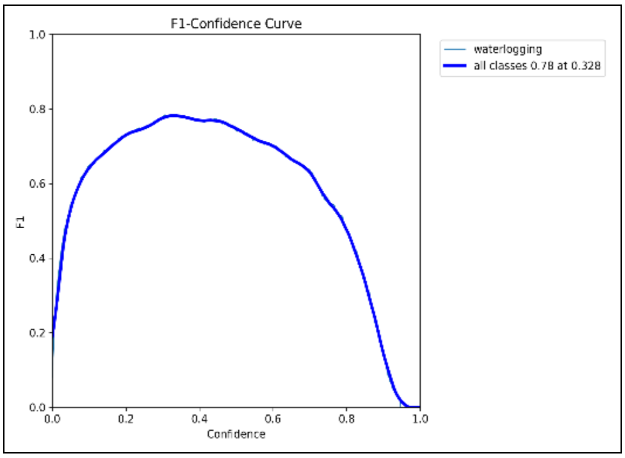

Figure 3. F1-Confidence Curve

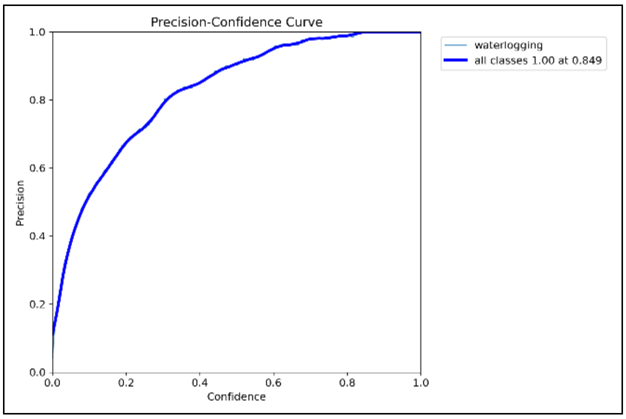

Figure 4. Precision-Confidence Curve

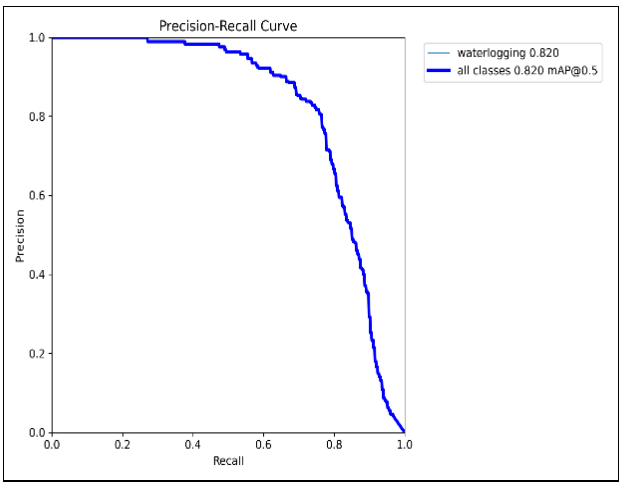

Figure 5. Precision-Recall Curve

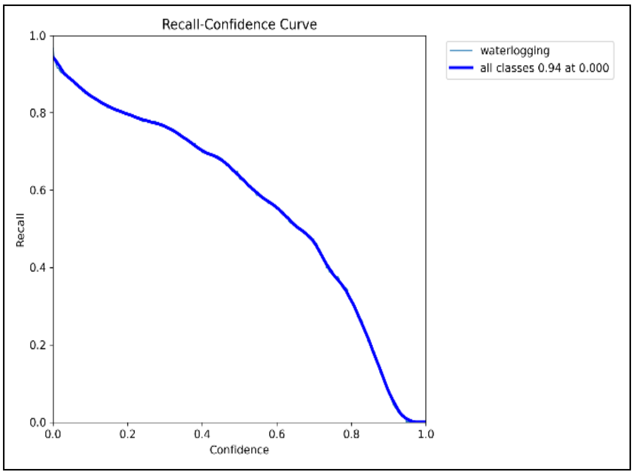

Figure 6. Recall-Confidence Curve

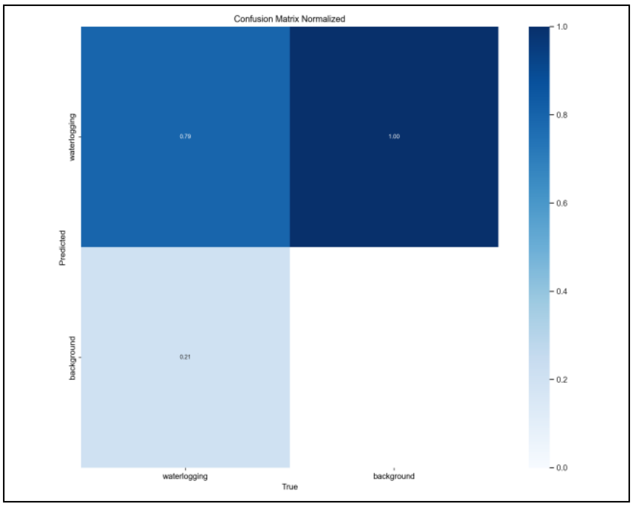

Figure 7. Confusion Matrix

Figures 3 to 7 illustrate the model performance through different evaluation curves across varying confidence thresholds. Figure 3 presents the F1-Confidence Curve, pinpointing the threshold where precision and recall achieve an optimal balance, indicating the most reliable point for waterlogging detection. Figure 4 shows the Precision-Confidence Curve, demonstrating how the model precision tends to improve as the confidence threshold for positive predictions increases. Figure 5 depicts the Precision–Recall Curve, highlighting the balance between precision and recall at different threshold levels. Figure 6 illustrates the Recall-Confidence Curve, revealing that recall typically decreases as the confidence threshold becomes more stringent. Figure 7 shows the confusion matrix for YOLOv11, providing a visual summary of the model performance in waterlogging detection. The experimental setup is shown in Table 2.

Component	Details
Hardware	CDAC PARAM Siddhi-AI NVIDIA A100-SXM4 (1 × GPUs, 40 GB)
Memory	64 GB
OS	Ubuntu 22.04.4 LTS
Software Stack	Ultralytics 8.3.62, Python-3.9.21, torch-2.5.1+cu118
Dataset	1000 images of waterlogged road
Input Image Size	640*640
DNN Model	YOLOv11 (yolo11n-seg.pt)
Epochs	200
Optimizer	AdamW (lr = 0.002, momentum = 0.9)
Batch Size	4
Metrics	Precision, Recall, F1 Score, Accuracy and IoU
Parameters	355 layers, 2,842,803 parameters, 2,842,787 gradients, 10.4 GFLOPs
Training time	21 minutes

Table 2. Experimental setup

5.3 Testing and Evaluating DNN Model

The trained model was evaluated on a test dataset of 200 images to detect waterlogging. The evaluation was done using metrics such as accuracy, precision, recall, F1-score, and IoU, which are critical for assessing overall detection effectiveness. The performance metrics along with their respective formulas are detailed below:

- Accuracy calculated as the ratio of accurately predicted vs the total number of predictions, indicating the overall efficacy of the model.

  Accuracy = (tp + tn) ÷ (tp + tn + fp + fn)

- A high precision value indicates that most of the predicted results are accurate. Precision was calculated as below:

  Precision = tp ÷ (tp + fp)

- Recall refers to the number of ground truth instances correctly recognized by the model. Recall was calculated as below:

  Recall = tp ÷ (tp + fn)

- The F1 score is useful in situations where there is a class imbalance. F1 was calculated as below:

  F1 Score = 2 × (Precision × Recall) ÷ (Precision + Recall)

- The IoU measures the extent of overlap between the predicted mask and the ground truth. IoU was calculated as below:

  IoU = tp ÷ (tp + fp + fn)

Where, tp denotes True Positives, tn denotes True Negatives, fp denotes False Positives, and fn denotes False Negatives.

6. Result and Discussion

The model was trained to accurately segment waterlogged areas in rural regions of India. Training was conducted over 200 epochs, and with early stopping applied, the optimal model was obtained at the 66th epoch. Figure 8 illustrates the evaluation metrics-based performance analysis of DNN model.

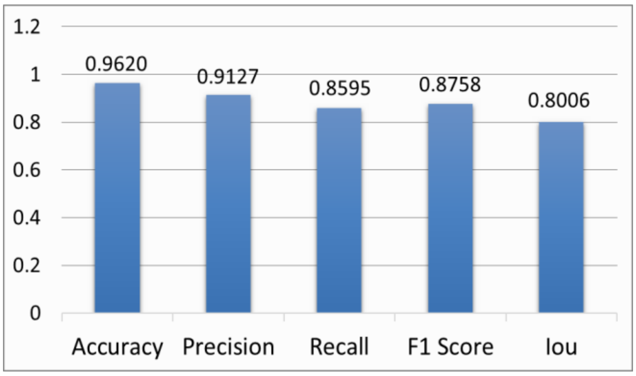

Figure 8. Evaluation metrics-based performance analysis

The model outcome on the test dataset is given below:

- Accuracy: 96.20%
- Precision: 91.27%
- Recall: 85.95%
- F1 Score: 87.58%
- IoU: 80.06%

It is observed that the output model is effective in detecting waterlogging on road. An accuracy of model is 96.20% which confirms that model identifies most pixels correctly. The precision 91.27% shows that low false positive which means model rarely misidentifies non waterlogged region as waterlogged region. Recall of 85.95% signifies model successfully identifies majority of actual waterlogged areas. F1 score 87.58% means model has very good balance between precision and recall which indicates model is performing very well on segmentation task. Furthermore, IoU is 80.06% means model prediction matches the ground truth very closely.

However, there are several challenges like difference in light and shadows, reflective surfaces and vegetation interference while detecting waterlogging but architecture of YOLOv11 is having enhanced backbone and improved head design to overcome these challenges. It is observed that YOLOv11 has better performance in both speed and accuracy. Figure 9 illustrates four input images along with their corresponding outputs generated by YOLOv11. The images show identified waterlogging, with segmentation indicating confidence scores 75%. Lowering the confidence level increases false positives, while raising it reduces true positives, so an optimal confidence level is necessary. Figure 9 represents the qualitative outcome of the deep learning model.

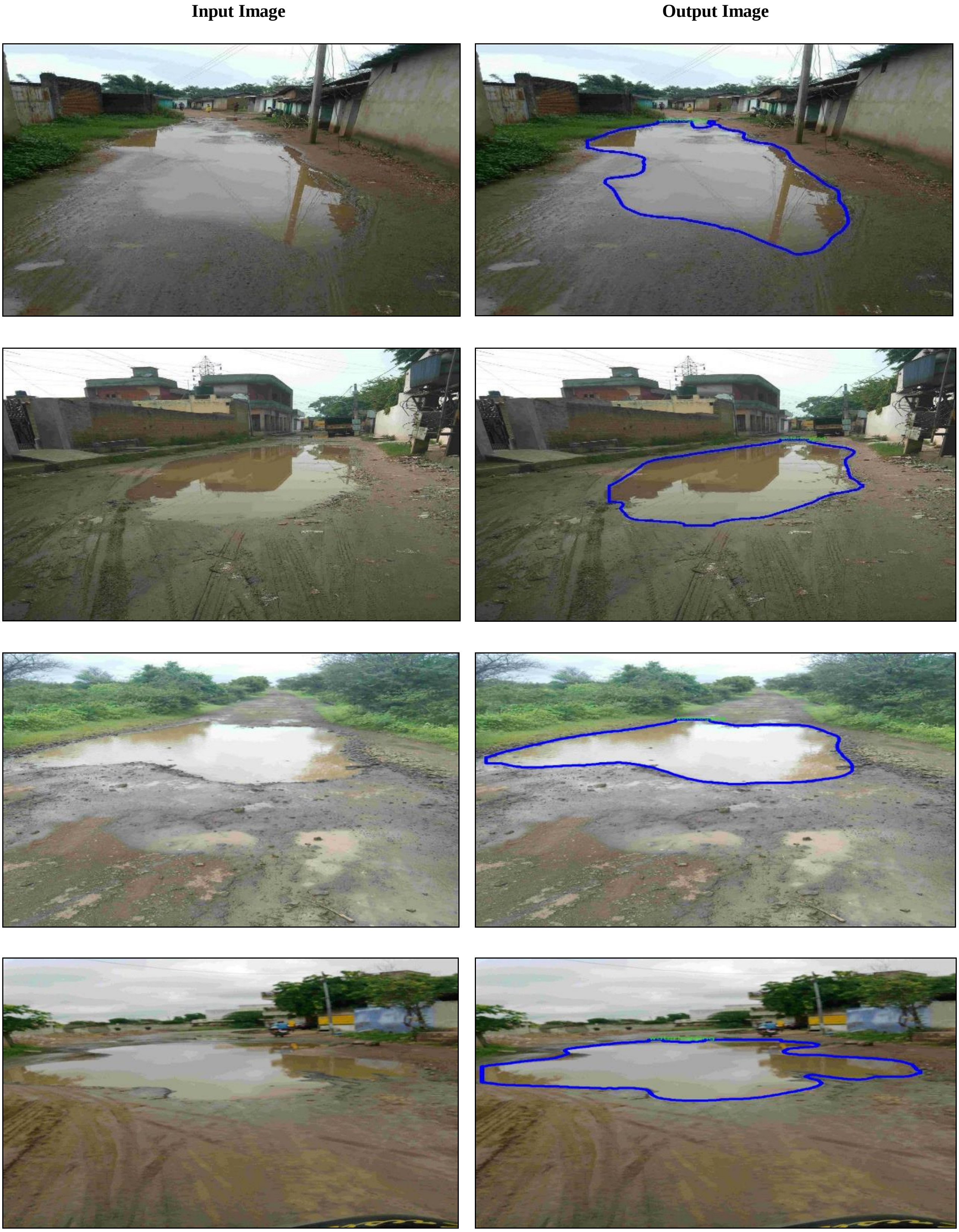

Figure 9. Output of DNN for four samples (blue boundary shows waterlogged regions)

7. Conclusion

This paper utilized segmentation-based deep learning model for waterlogging detection from road images. Owing to the dearth of datasets, we have prepared annotated dataset of waterlogging. Our model achieved a precision of 91.27%, and IoU of 80.06%. This approach is both cost-effective and reliable, highlighting the promising potential of DNNs for waterlogging detection. We recommend its potential integration into national programs like the PMGSY National GIS. In future, experimentation could extend to video data for waterlogging detection on road. Further efforts are needed to accurately identify the geographical locations of waterlogging in real-time on road, enabling their utilization for road maintenance and enhancing public safety.

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References

He, D., Yuan, H., Zhang, G. and Huang, W., 2021. March. The Monitoring System of Urban Road Waterlogging Depth with Smart Lamp Pole. In 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE).pp. 664-667). IEEE.

Islam, M.M., Mahamud, M.S., Salsabil, U., Amin, A.A.M. and Suman, S.H., 2024. An IoT Based Water-Logging Detection System: A Case Study of Dhaka. arXiv preprint arXiv:2403.18949.

Lo, S.W., Wu, J.H., Chang, J.Y., Tseng, C.H., Lin, M.W. and Lin, F.P., 2021. Deep sensing of urban waterlogging. IEEE Access, 9, pp.127185-127203.

Song, S., Zhang, C., Zhang, P., Li, P., Song, F. and Zhang, L., 2024. September. Urban Waterlogging Detection: A Challenging Benchmark and Large-Small Model Co-adapter. In European Conference on Computer Vision.Cham: Springer Nature Switzerland. pp. 366-382.

Starke, M. and Geiger, C., 2022. Machine vision based waterlogged area detection for gravel road condition monitoring. International Journal of Forest Engineering, vol. 33(3), pp.243-249.

Xiong, L., Feng, X., Zhang, L., Sun, Q. and Ren, H., 2024. September. Semantic Segmentation Algorithm of Nighttime Road Surface Water Based on Improved Low-Light Image Enhancement. In 2024 5th International Conference on Intelligent Computing and Human-Computer Interaction (ICHCI).pp. 104-108. IEEE.

Zheyu, Z., Suigao, Y. and Chengbin, L., 2013, June. Research on Water-Related Issues in Urban Road System. In 2013 Fourth International Conference on Digital Manufacturing & Automation (pp. 1148-1151). IEEE.

Zhu, J., Liu, F., Xue, Z., Luo, W., Peng, H., He, J., Fu, Z. and Luo, D., 2024. Cable Tunnel Waterlogging Detection for Low-Light and Interference Based on Three-Stage Recognition. IEEE Access.

Khanam, R. and Hussain, M., 2024. YOLOv11: An Overview of the Key Architectural Enhancements. arXiv e-prints, pp.arXiv-2410.