Enhancing Unpaved Road Condition Monitoring in Uganda Using Smartphone Imagery and Deep Learning

Obalim G.[1]*, Tokunaga M.[2]

Department of Civil and Environmental Engineering, Graduate School of Engineering, Kanazawa Institute of Technology, Japan

INTRODUCTION

Uganda's 150,000 km road network is the backbone of rural life, yet most of it remains unpaved and highly vulnerable to rainfall, erosion, and heavy traffic. Manual inspections are slow and expensive, often delaying repairs and increasing long-term costs. National policies such as Vision 2040 and the upcoming NDP IV stress the need for resilient, technology-driven infrastructure, aligning with SDG 9. Affordable image-based methods, powered by AI and smartphones, offer a practical alternative to traditional surveys.

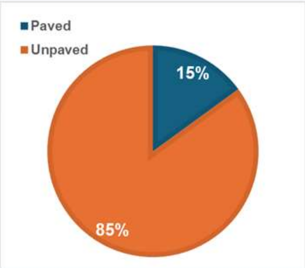

Figure 1: Percentage share of Uganda paved and unpaved roads

OBJECTIVES

The purpose of this study is to demonstrate that something as simple and affordable as a smartphone, combined with the power of deep learning, can deliver reliable road condition assessments. The framework is designed to detect and map road surfaces, while also identifying critical defects such as potholes, rutting, erosion, and weed encroachment. Ultimately, the aim is to produce decision-ready maps and condition reports that road authorities can use for smarter, faster, and more cost-effective maintenance planning.

METHODOLOGY

The research followed a structured workflow that began with field image collection across district and community roads in Uganda. Using a dashboard-mounted smartphone and occasionally handheld captures, thousands of geo-referenced RGB images were collected in both wet and dry seasons. This approach was chosen because it is affordable, easy to replicate, and does not require the specialized permissions and costs often associated with drones.Annotations were prepared using tools such as the Roboflow platform and the VIA (VGG Image Annotator). A two-stage deep learning pipeline was implemented using YOLOv8, a state-of-the-art object detection and segmentation model. The first stage of the pipeline focused on separating road surfaces from their surroundings—such as vegetation, sky, or roadside features. The second stage refined the process further by isolating specific defects within the road surface, including cracks, potholes, and other visible signs of distress. Evaluation of the models relied on standard performance metrics such as precision, recall, F1-score, and mean average precision (mAP). This ensured that the models were assessed not only for their ability to correctly identify defects but also for their robustness across different conditions.

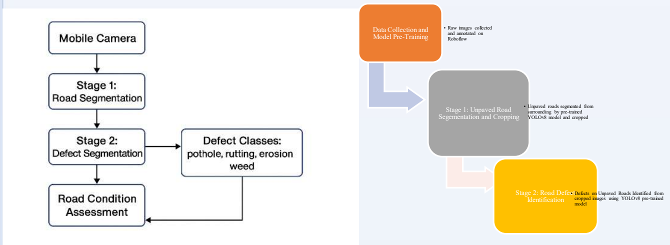

Figure 2: Simplified schematic representation of the research method

Figure 3: Stage 1 annotations, with VIA (left), and with Roboflow (right)

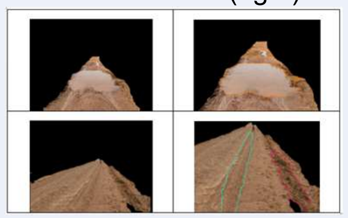

Figure 4: Stage 2 defect dataset samples

RESULTS

The first stage of the YOLOv8 segmentation model produced highly encouraging results. With a dataset of just over 350 images, the model achieved an F1-score of 0.92, precision of 1.00, and recall between 0.97 and 0.98. The mean average precision at IoU 0.5 reached 0.96, while performance at stricter thresholds (mAP@0.5–0.95) remained within the 0.75–0.77 range. In practical terms, the system correctly identified unpaved road segments in 88 percent of cases, while background areas such as sky or vegetation were classified perfectly.The second stage, which focuses on road defects, is still being refined but is already showing promising results. Pilot experiments using 50 images produced F1-scores exceeding 0.80 across multiple defect categories. These outcomes demonstrate that even with relatively modest datasets, the method can achieve accuracy levels that rival UAV-based approaches while requiring only a smartphone.

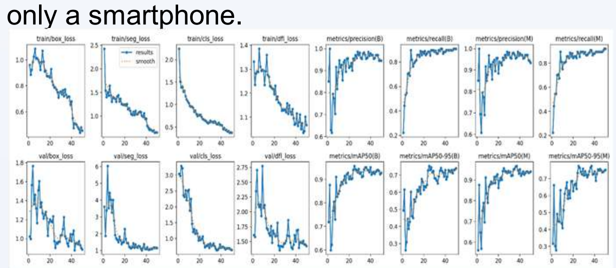

Figure 5: Training and validation performance curves

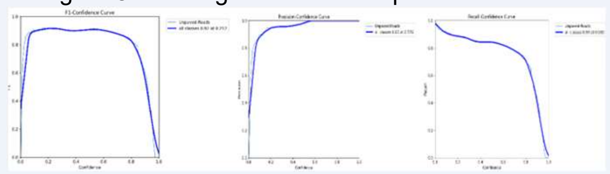

Figure 6: Precision–Recall and F1-score curves

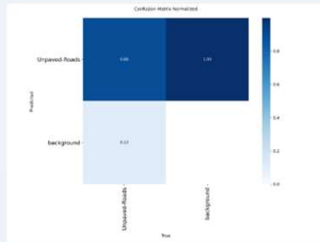

Figure 7: Stage 1 confusion matrix

Metric	Value (Best Epoch)
F1 Score (0.21 conf.)	0.92
Precision (0.57 conf.)	1.00
Recall (0.0 conf.)	0.97–0.98
mAP@0.5	0.96
mAP@0.5–0.95	0.75–0.77
Unpaved Road detection	88 % correct, 12 % missed
Background detection	100 % correct

Table 1: Summary of Key Metrics (Stage 1)

CONCLUSION

This research demonstrates that smartphone imagery combined with modern deep learning methods can achieve accurate, reliable, and affordable assessments of unpaved roads. The framework achieves high precision in surface detection, while defect detection shows strong early promise. With continued refinement—such as semi-supervised learning, integration with UAV or satellite imagery, and the release of open datasets—the system can become even more robust.Most importantly, it offers a scalable solution that resource-constrained countries can adopt without heavy investment. In doing so, it supports smarter maintenance, lowers life-cycle costs, and contributes directly to the realization of Uganda's Vision 2040, the National Development Plan IV, and the UN Sustainable Development Goals.

REFERENCES

1. Liu, Z., Wu, W., Gu, X., Li, S., Wang, L., & Zhang, T. (2021). Application of combining yolo models and 3d gpr images in road detection and maintenance. Remote Sensing, 13(6), 1–18. https://doi.org/10.3390/rs13061081

2. Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H. (2018). Road Damage Detection and Classification Using Deep Neural Networks with Smartphone Images. Computer-Aided Civil and Infrastructure Engineering, 33(12), 1127–1141. https://doi.org/10.1111/mice.12387

3. Nasiruddin Khilji, T., Lopes Amaral Loures, L., & Rezazadeh Azar, E. (2020). Distress Recognition in Unpaved Roads Using Unmanned Aerial Systems and Deep Learning Segmentation.

4. National Planning Authority (NPA). (2024). National Development Plan IV (2025–2030): Draft for consultation. Government of Uganda.

5. Obeti, A. M., Muhwezi, L., Kakitahi, J. M., & Byaruhanga, C. B. (2024). Investigating the cost of mechanized unpaved road maintenance operations in Uganda. Transportation Research Interdisciplinary Perspectives, 25. https://doi.org/10.1016/j.trip.2024.101135

6. Obunguta, F., & Matsushima, K. (2022). Optimal pavement management strategy development with a stochastic model and its practical application to Ugandan national roads. International Journal of Pavement Engineering, 23(7), 2405–24https://doi.org/10.1080/10298436.2020.1857759

7. Rateke, T., & von Wangenheim, A. (2021). Road surface detection and differentiation considering surface damages. Autonomous Robots, 45(2), 299–312. https://doi.org/10.1007/s10514-020-09964-3

8. Tripathi, R., Indu, S., & Kumar, R. (2025, in press). Unpaved road damage detection via semantic segmentation: Enabling smarter ADAS. Journal of Intelligent Transportation Systems.

9. Ultralytics. Instance Segmentation. Ultralytics. Retrieved August 15, 2025, from https://docs.ultralytics.com/tasks/segment/

CONTACT

geraldobalim@gmail.com
+256-777581599/+81-08042532278