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

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Abstract: Uganda maintains roughly 150,000 km of roads, yet over 85 percent remain unpaved, leaving much of the network vulnerable to weather-related wear and traffic damage. Limited budgets, slow manual inspections, and the lack of up-to-date condition data make it difficult to plan timely and cost-effective maintenance. To address these challenges, this study develops a low-cost, smartphone-based deep learning framework for monitoring the condition of unpaved roads. Using geo-referenced images collected from a smartphone camera, the system applies a two-stage YOLOv8 segmentation process, assisted by the Roboflow platform for image annotation. Stage 1 identifies and maps unpaved road surfaces with high accuracy, reaching an F1 score of 0.92 and mAP@0.5 of 0.96. Stage 2, which is now in progress, focuses on the detailed segmentation of defects such as potholes, rutting, erosion, and weed encroachment, with early tests already showing encouraging results above 0.70 precision values. The outputs closely match expert field assessments and are being prepared for integration with QGIS to enable spatial visualization and decision-ready mapping. By providing objective, near–real-time assessments, the framework supports better targeting of maintenance resources, reduces life-cycle costs, and lays the groundwork for driver-assist and autonomous navigation in rural settings where high-definition maps are unavailable. Offering a combination of affordability, accuracy, and scalability, this approach directly supports Uganda's national infrastructure goals and provides a model that can be adapted in other regions seeking sustainable, technology-driven road management.

Keywords: deep learning, road condition monitoring, smartphone imagery, unpaved road

1. Introduction

Uganda's 150,000 km road network is the backbone of national trade, tourism, and rural livelihoods, yet over 85 % remains unpaved, leaving it vulnerable to heavy rains and constant traffic wear (Obeti et al., 2024; Obunguta & Matsushima, 2022).

Recognizing that dependable transport is key to growth, the government's Vision 2040 and National Development Plan IV (2025–2030) call for first-class, climate-resilient infrastructure, aligning with United Nations Sustainable Development Goal 9, which promotes resilient and innovative infrastructure (NPA, 2013; NPA, 2024; United Nations, 2015).

Maintaining this vast unpaved network is costly and slow. Manual inspections cost roughly USD 7000–9000 per kilometre, are labor-intensive, and often delay repairs—leading to premature road failure and higher life-cycle costs (Obunguta, 2023; Saha & Ksai, 2017).

Studies demonstrate that smartphone-mounted cameras can detect road defects with F1 scores above 0.85 (Maeda et al., 2018; Zhang et al., 2022), and next-generation hybrid detection–segmentation models like YOLOv8 can map complex, unstructured road surfaces in real time (Liu et al., 2021; Tripathi et al., 2025).

For unpaved contexts, UAV-based methods achieve IoU rates beyond 93 % (Nasiruddin Khilji et al., 2020); but their cost and regulatory hurdles limit routine use.

Economic studies confirm that timely, image-based monitoring can substantially cut maintenance budgets (Obeti et al., 2024).

Despite this progress, gaps remain: most prior research targets paved roads or simple binary classification (Pereira et al., 2018), and few integrate instance segmentation with national policy goals and life-cycle cost models.

This study addresses these gaps with a two-stage YOLOv8 segmentation framework applied to district roads in Northern Uganda. Stage 1 accurately maps unpaved road surfaces. Stage 2 (in progress) segments critical defects such as potholes, rutting, erosion, and weed encroachment.

By using geo-referenced images from a dashboard-mounted smartphone, the framework provides near-real-time, objective assessments that support Vision 2040, NDP IV, and SDG 9, improve maintenance prioritization, and create a data foundation for future driverless-navigation and intelligent transport systems.

2. Methodology

This study develops a low-cost, scalable framework for unpaved-road condition assessment using consumer-grade smartphone images and deep learning (Maeda et al., 2018; Tripathi et al., 2025).

The workflow (Figure 1) combines field imaging, camera calibration, two-stage dataset creation, and YOLOv8 model training.

District and community roads across Uganda were photographed in both wet and dry seasons, covering lightly used and heavily eroded segments.

A smartphone mounted on a dashboard or used handheld captured thousands of RGB images at varied pitch angles and distances, following approaches in Pereira et al. (2018).

This ground-level imaging is inexpensive yet provides deep-learning-ready data compared to UAV surveys (Nasiruddin Khilji et al., 2020).

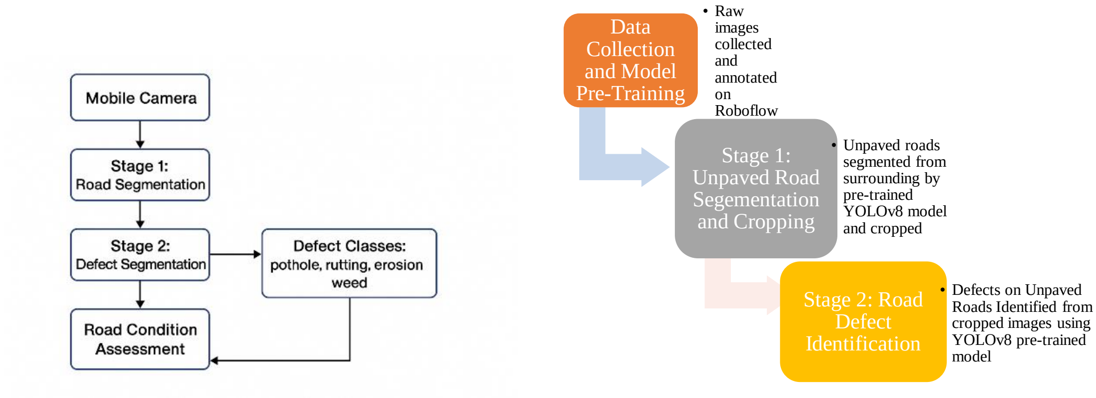

Figure 1: Simplified schematic representation of the research method

A two-stage pipeline (Nasiruddin Khilji et al., 2020; Tripathi et al., 2025) simplified complex surface analysis:

Stage 1 – Road Surface: 360 images (247 training, 71 validation, 35 testing) were pixel-labeled in Roboflow to separate road surfaces from vegetation, sky, and buildings (Rateke & von Wangenheim, 2021)

Figure 2: Stage 1 annotations, with VIA (left), and with Roboflow (right)

Stage 2 – Road Defects: The Stage 1 model segmented 1,700 additional images; cropped road regions form a defect-focused set for pothole, rutting, erosion, and weed detection. An initial trial (50 images) is summarized below.

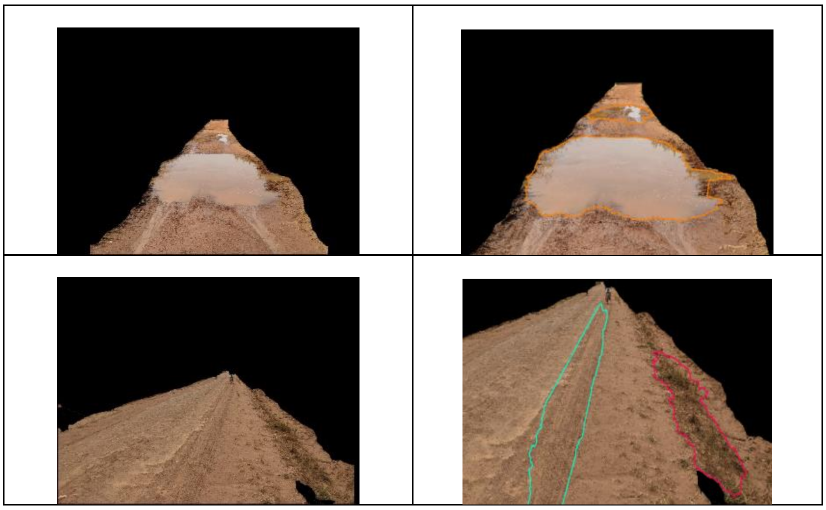

Figure 3: Stage 2 defect dataset samples

YOLOv8 (Ultralytics, 2023) was chosen for its accuracy–speed balance and integrated instance segmentation (Zhang et al., 2022).

Evaluation used precision, recall, F1, and mean average precision at multiple IoU thresholds, supported by confusion-matrix analysis (Maeda et al., 2018).

By merging computer vision with transportation economics and intelligent-vehicle research, the approach is both scientifically robust and practical for scalable rural road asset management.

3. Results

The YOLOv8 segmentation model trained on 353 Stage 1 images (247 training, 71 validation, 35 testing) converged smoothly.

At epoch 25, box, segmentation, classification, and distribution losses fell to 0.78, 1.11, 0.65, and 1.16, with similar validation values, showing minimal overfitting.

Detection accuracy was strong—mAP@0.5 of 0.96, mAP@0.5–0.95 approx. 0.75–0.77—exceeding U-Net and DeepLab benchmarks (F1 approx. 0.80–0.85; mAP@0.5 approx. 0.85–0.90) reported by (Liu et al., 2021) and (Rateke & von Wangenheim, 2021)

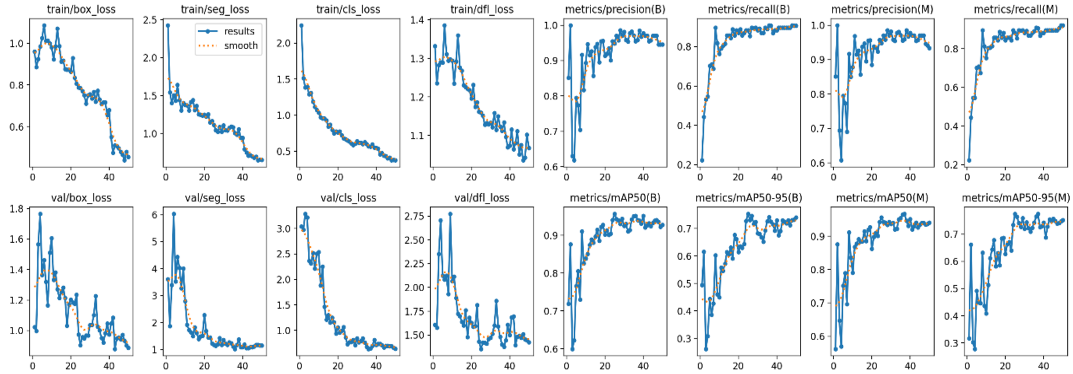

Figure 4: Training and validation performance curves

Performance analysis (Figure 5) confirmed flexible deployment: F1-score was 0.92 at a 0.21 confidence threshold balanced false positives/negatives. Precision achieved 1.00 at 0.57 confidence supported strict maintenance planning. Recall showed 0.97–0.98 at 0.0 confidence captured nearly all surfaces.

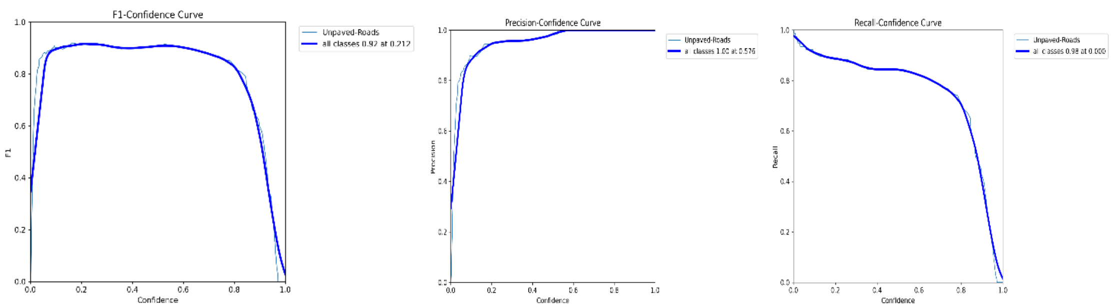

Figure 5: Precision–Recall and F1-score curves

The confusion matrix (Figure 6) showed 88 % correct unpaved-road detection and 100 % background classification, reflecting the robust, seasonally varied data pipeline.

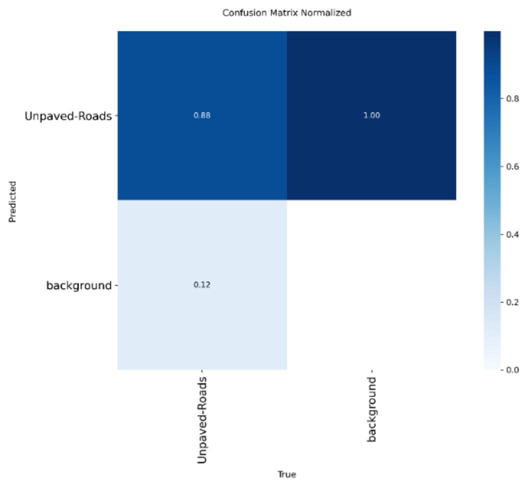

Figure 6: Stage 1 confusion matrix

This work extends low-cost, vision-based road assessment. Earlier smartphone studies (Maeda et al., 2018; Pereira et al., 2018) and UAV-based segmentation (Nasiruddin Khilji et al., 2020) reported similar results.

Our Stage 1 model, using only smartphone data, achieved F1 of 0.92 and mAP@0.5 of 0.96, surpasses these baselines and confirms YOLO architectures' suitability (Zhang et al., 2022; Tripathi et al., 2025). High-fidelity masks strengthen localization and path planning, anticipate obstacles even on vegetated tracks, and rely only on a low-cost dash-mounted smartphone, offering an affordable data source for rural ADAS and autonomous logistics (Tripathi et al., 2025).

Stage 2 will segment potholes, rutting, erosion, and weeds; pilot F1 scores already exceed 0.80. Integration of UAV data and semi-supervised methods will improve geometry and reduce labeling. Remaining challenges include narrow or vegetation-covered tracks and seasonal drift.

Table 1: Summary of Key Metrics (Stage 1)

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

4. Conclusion

This study shows that ordinary smartphones combined with deep learning can monitor unpaved roads accurately and at very low cost. A two-stage YOLOv8 model, annotated in Roboflow and tested on district roads in Northern Uganda, achieved strong, consistent performance without specialized hardware. By automating what are now slow, manual inspections, the framework supports Uganda's Vision 2040, the National Development Plan IV, and UN Sustainable Development Goal 9, all of which emphasize climate-resilient and innovative transport infrastructure.

The system's road-surface masks also aid driver-assist and autonomous navigation in rural areas lacking high-definition maps. Requiring only a dashboard-mounted phone and modest data, it remains practical and affordable even where internet access is limited. The model delivers precise defect information, helping agencies target maintenance, lower life-cycle costs, and extend road service life. Some challenges persist, including shadows, seasonal changes, and narrow or overgrown tracks. Planned improvements—such as semi-supervised learning, domain adaptation, UAV or satellite imagery, and a Stage 2 module for detailed defect detection—aim to boost accuracy. A public dataset release will further support research and adaptation of this approach across Africa, Asia, and Latin America.

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