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Smartphone-Based Real-Time Cyclist Safety System Using Lightweight YOLOv5n Object Detection

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Abstract : Cyclist fatalities are increasing globally—1,155 deaths were recorded in the US alone in 2023. Many of these incidents involve single-bicycle crashes caused by road hazards such as potholes, debris, or animals. This paper presents a smartphone-based real-time hazard detection system designed to enhance cyclist safety by providing timely warnings using a lightweight AI model. The system leverages YOLOv5n, an ultra-efficient object detection model optimized with TensorFlow Lite and OpenCV.

YOLOv5n was selected over other lightweight models like MobileNet SSD or YOLOv6-lite for three reasons: (1) it offers a superior balance of inference speed and detection accuracy on mid-range smartphones; (2) its modular PyTorch implementation and quantization pipelines are deployment-friendly; and (3) it consistently outperformed MobileNet SSD in detecting small hazards while using less memory than YOLOv6-lite.

The system detects both static (e.g., potholes, debris) and dynamic (e.g., vehicles, pedestrians) hazards from live video streams and issues alerts. Trained on a curated dataset of 2,000+ images, it achieved a mean Average Precision (mAP@0.5) of 0.86 and operated at 12.8–13.4 FPS on mid-range smartphones. Field tests showed an alert lead time of 1.2 ± 0.2 seconds, enhancing rider response and braking time. This can reduce impact risk by over 35% in urban cycling conditions [1].

Unlike server-based or embedded alternatives, this privacy-preserving solution runs entirely on-device. Aligning with Vision Zero and sustainable mobility goals [2], it can integrate into municipal hazard systems or cyclist insurance incentives, fostering both safety and behavioral accountability.

1. Introduction

Urban cycling has grown due to health and sustainability benefits, but cyclists remain vulnerable to hazards like potholes, debris, animals, and pedestrians. Unlike cars with ADAS, bicycles have no onboard computing or consistent power sources. Mounting complex hardware reduces comfort and raises cost.

This project addresses those gaps with a smartphone-only solution powered by an AI model that runs in real time on mid-range Android devices. The aim is to offer a scalable, affordable, and privacy-respecting hazard alert system. The paper also emphasizes public accessibility, given the limited funding and awareness dedicated to cyclist safety.

2. Related Work

Past work includes bulky embedded systems using ultrasonic sensors, thermal cameras, or LIDAR [3], as well as server-dependent object detection [5]. However, these compromise portability or privacy.

Lightweight CNNs like MobileNetV3 [6] and EfficientDet offer better latency–accuracy trade-offs but are rarely optimized for cyclists. YOLOv5n strikes a balance for mobile deployment. Prior studies have used YOLO in automotive safety [4], but its feasibility for on-phone cyclist safety remains underexplored.

3. System Overview

3.1 Architecture

- **Input**: 720p smartphone camera stream
- **Detection**: YOLOv5n (TensorFlow Lite)
- **Processing**: Bounding box size + expansion across frames
- **Output**: Audio/visual/vibration alert

Figure 1. System architecture from camera input to alert generation

YOLOv5n was quantized to float16 via post-training optimization (PyTorch → ONNX → TF SavedModel → TFLite), significantly reducing size and inference latency.

Future iterations may incorporate monocular depth estimation via MiDaS v3 or MobileDepth, but such integrations are still under experimental review due to compute cost on budget devices.

3.2 Feature Set

- Detects potholes, debris, pedestrians, animals
- Approximates distance via bounding box scaling
- Customizable alerts
- Detection logging
- Optional fitness app integration (e.g., Strava, Google Fit)

4. Implementation Details

The model was trained with transfer learning on a YOLOv5n base using a custom dataset of 2,000+ images. Data augmentation (e.g., CLAHE, rotation) improved generalization. Final deployment was tested on Android devices.

Figure 2. Detection output showing pothole and vehicle alert

Optimizations:

- Quantized TFLite model
- Jitter-filtering alert logic
- CPU/memory usage verified via Android Studio Profiler

5. Results and Evaluation

5.1 Device Benchmark Summary

Device	**FPS**	**Inference Time**	**CPU Load**	**Battery Drain (10 min)**	**Notes**
Redmi Note 10 Pro	12.8	78 ms	~71%	~5%	Production baseline
Samsung A51	11.2	91 ms	~76%	~6%	Slightly slower
Pixel 6a	14.3	68 ms	~66%	~4%	Best performer

Table 1. On-device performance metrics across 3 Android smartphones

5.2 Detection Accuracy by Class

- Potholes – Precision: 92%, Recall: 89%
- Debris – Precision: 84%, Recall: 81%
- Pedestrians – Precision: 88%, Recall: 86%
- Animals – Precision: 79%, Recall: 76%

5.3 Other Metrics

- **FPR**: 7.5%
- **Alert Lead Time**: 1.2 ± 0.2 seconds
- **Power Use**: ~110 mW (~4.2 mAh/min)
- **Model Storage**: 23.6 MB
- **Stability**: 3+ hours continuous use crash-free

Figure 3. Missed detection in low-light scenario

6. Limitations

1. Reduced accuracy in low-light/night settings
2. Missed detection of small debris/cracks
3. Blur from motion or shaky mounts
4. Short-lived dynamic object visibility (e.g., fast animals)
5. Dataset may lack geographic variability
6. Power consumption in extended rides
7. Weather interference (rain, fog, glare)
8. Occasional frame drops on low-end devices
9. Mild overfitting on urban scenes
10. Limited Android hardware support

Mitigations include CLAHE preprocessing, smoothing, synthetic augmentation, and community-submitted training data.

7. Conclusion and Future Scope

This study proposes a real-time hazard detection system that:

- Runs on-device with YOLOv5n
- Provides 0.86 mAP and 12.8–13.4 FPS
- Offers ~1.2 s lead time for improved reaction

Deployment Models:

- Android app
- SDK for cycling apps
- API for municipal integration
- B2G partnerships

Roadmap:

- Lightweight depth estimation
- Federated learning
- Gamified citizen reporting
- Real-time hazard heatmaps

Aligned with Vision Zero goals, this system is patent-pending and ready for urban-scale implementation.

8. References

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9. About the Author

Gautam Rulyan is an independent researcher and student with a strong interest in artificial intelligence, computer vision, and applied machine learning. He is a qualified IOQM candidate, published researcher at IJRASET, and a perfect scorer in the Aryabhatta Mathematics Competition. Gautam is also a recipient of the SAMSO AIR-2 distinction and is currently pursuing his B.Sc. IT studies while preparing for international university admissions. His focus lies in developing lightweight AI applications for real-world impact, and he is actively working on patent-pending innovations in the domain of cyclist safety and real-time mobile vision systems.