AI-Powered Driveway Safety System: Preventing Child Accidents with Computer Vision

An innovative solution to prevent driveway accidents, especially involving children.

By: Alfredo A. Torrena Jr.
Eunseok Choi
Fabricio Mello Mulato
Yan Huang

Safekids New Zealand. (2011). *Safekids New Zealand position paper: Child driveway run over injuries*. Safekids New Zealand.

The Problem: Driveway Accidents

1. **Serious Issue**

   Driveway accidents are a significant safety concern, particularly for children under 5.

2. **System Limitations**

   Existing systems often fail to detect small or occluded objects.

3. **NZ Statistics**

   In New Zealand alone, 5 children are killed or seriously injured each year in driveways.

Our AI-powered system aims to provide real-time risk detection using computer vision.

Otago Daily Times Online News. (2025). Road toll rises as toddler killed in driveway [Accessed: Jun. 30, 2025]

Literature Review: Related Work & Gaps

Related Work

- Leone et al.: Smart surveillance with edge devices.
- Sazid & Afsha: High test accuracy, but lacks real-world testing.
- Redmon et al.: YOLO is fast but weak with small/crowded objects.
- Lakshmi et al.: Struggles in occluded/low-light conditions.

Gaps Identified

- Poor real-world performance.
- Lack of small object detection.
- Limited deployment on embedded hardware.
- No standard metrics across studies.

Literature Review: Related Work & Gaps

Related Work

- Xu et al. proposed a lightweight YOLOv3, but not for pedestrian detection.
- Reddy et al. used image processing with Cascade Random Forest to detect pedestrians, but the system was limited to specific conditions like summer driving.
- Monika et al. used YOLOv5 and pose-based models, but struggled with occlusion and motion changes.

Gaps Identified

- Lightweight models often fail with occlusion and urban complexity.
- Existing systems struggle with real-time detection under varied lighting and motion, making them unreliable for sudden pedestrian crossings
- Most methods rely on labeled data and fail in real-time dynamic ADAS situations.

Project Goals and Innovations

Objectives

- Detect people, children, and pets
- Provide adaptive alerts (visual, auditory, haptic).
- Reduce false positives with context awareness.
- Prevent accidents with timely warnings.

Innovations

- Optional sensor fusion (e.g., infrared).
- Edge computing via Raspberry Pi or Jetson Nano.
- Dashboard integration and alert customization.

Methodology – Model Development

Pre-trained Model

Used YOLOv5n pre-trained on COCO: 80 classes.

Custom Dataset

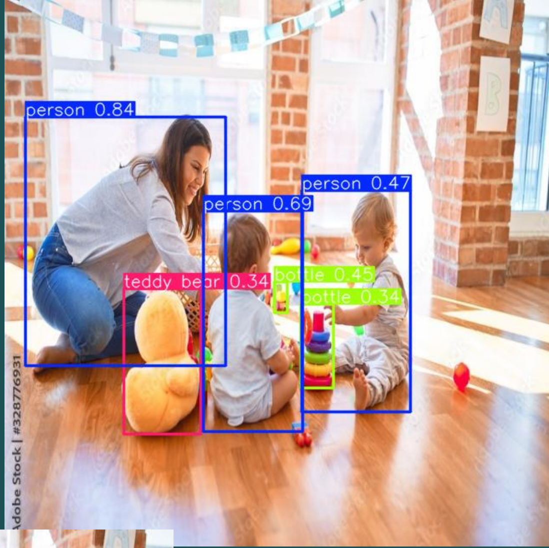
Added a new class: “kids” using a custom dataset (Roboflow).

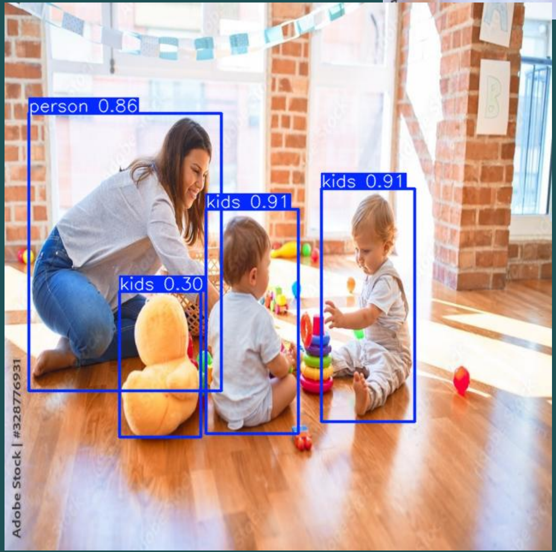
Transfer Learning

Applied transfer learning with layer freezing.

Training

Trained on a standard laptop with 50 epochs.





Methodology – System Design & Hardware

Architecture

Rear camera → Embedded device → Alert system

Embedded Options

- Raspberry Pi (~$75)
- Jetson Nano (~$100)

Software

Installed Python AI stack: NumPy, OpenCV, PyTorch, etc.

Alerts

Multimedia panel / direct brake control.

Results – Performance & Features

Features

- Real-time detection with visual/audio alerts.
- Confidence and frame threshold adjustments.
- Optional auto-braking at low speeds.

Performance

- Best performance at 0.4–0.6 confidence threshold.
- Fast processing: no significant latency.
- Limitations in poor light and crowded scenes.

Future Work & Conclusion

1 Future Enhancements

- Thermal + night vision camera integration.
- Larger, more diverse training data.
- Improved class separation with multi-scale models.
- Add haptic feedback to alert system.

2 Conclusion

- Functional, deployable prototype achieved.
- Ethical and privacy-conscious design.
- Strong foundation for real-world implementation.
- Socially valuable solution to a critical safety issue.