FYP02-DS-T2510-0035: ROAD BUMP DETECTION FOR IMPROVED DRIVER SAFETY USING DEEP LEARNING

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Abstract

Road anomalies such as speed bumps are critical for regulating traffic and ensuring safety. However, undetected or poorly marked bumps can result in vehicle damage or discomfort. This project proposes a deep learning-based detection system focusing on object detection models **YOLOv11, Faster R-CNN, and SSD**. Using a curated dataset and systematic model evaluation, the system demonstrates the potential for integration into intelligent driver-assistance systems (ADAS), enhancing both safety and comfort. The final prototype includes a web-based interface for model testing and visualization.

Problem Statement

- Environmental Variability: Speed bumps can be difficult to detect in low-visibility conditions such as at night, during adverse weather, or on poorly lit roads. Most systems relying solely on camera data can fail under these conditions, leading to false negatives or missed detections (Tithi et al., 2021).
- Insufficient Generalization Across Environments: Existing detection models may perform well in specific environments but struggle to generalize across a variety of road conditions, bump designs, or geographic regions. Models trained on limited datasets often fail when deployed in new contexts (Kaur & Singh, 2023).
- Computational Efficiency: Advanced detection models, particularly deep learning methods, require significant computational power. The real-time application of these models in autonomous vehicle systems can be challenging, as it requires processing capabilities that may not be available in embedded systems with low-latency constraints (Sharma et al., 2023).

Objectives

- Investigate Current Machine Learning Techniques.
- Develop a Deep Learning Model for Speed Bump Detection.
- Evaluate the Model's Performance.

Literature Review

Previous research has mostly focused on pothole detection (Maeda et al., 2018; Dutta et al., 2016), while speed bump detection remains less explored despite its importance in regulating speed and ensuring pedestrian safety. Deep learning offers a more robust solution, especially when models are trained on diverse datasets and fine-tuned for specific infrastructure types. Projects like Bala et al. (2021) highlight the effectiveness of deep models over traditional methods in real-world driving environments. By focusing on speed bump detection using deep learning, this project contributes to the growing field of intelligent road infrastructure analysis enhancing driver awareness and enabling the future of autonomous navigation.

Research Methodology

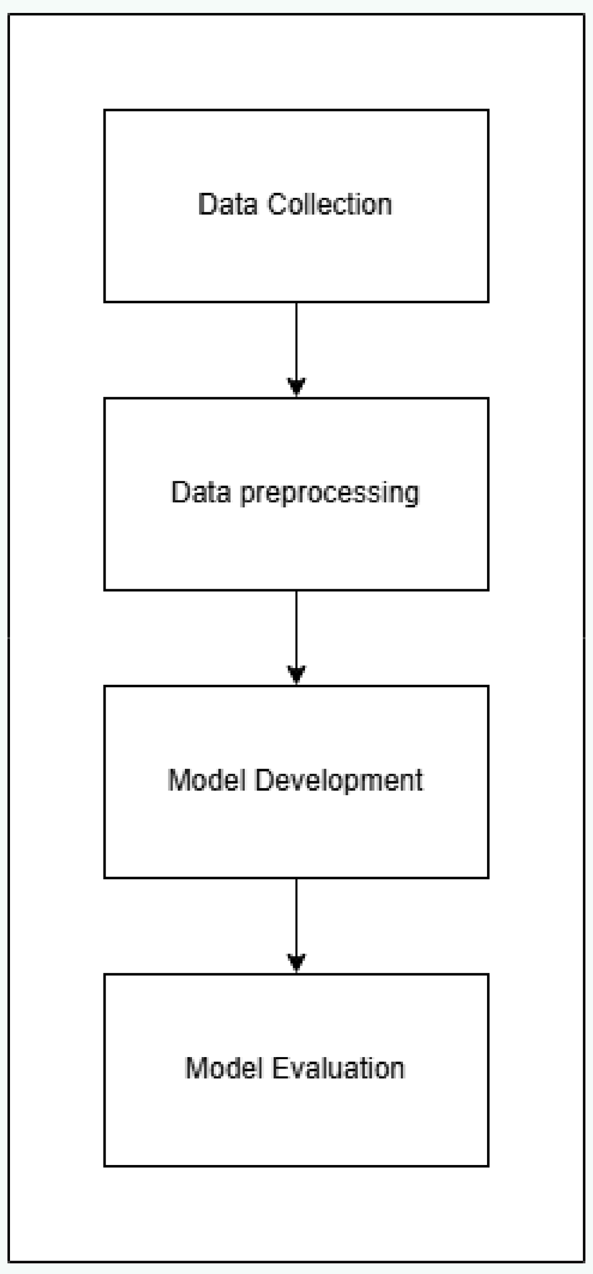
Data Collection:
Dataset was collected from multiple open-access sources such as image repositories on Roboflow and Kaggle.

Data Preprocessing:
Preprocessing involved data cleaning to remove irrelevant images, followed by manual annotation using Roboflow to mark the road bump locations with bounding boxes. The dataset was then split into training, validation and testing sets.

Model Development:
Three deep learning models were implemented to detect speed bumps in road images: YOLOv11, Faster R-CNN, and SSD.

Model Evaluation:
The models were evaluated using mean Average Precision (mAP), precision, recall, F1 Score and accuracy.

Framework of Road Bump Detection

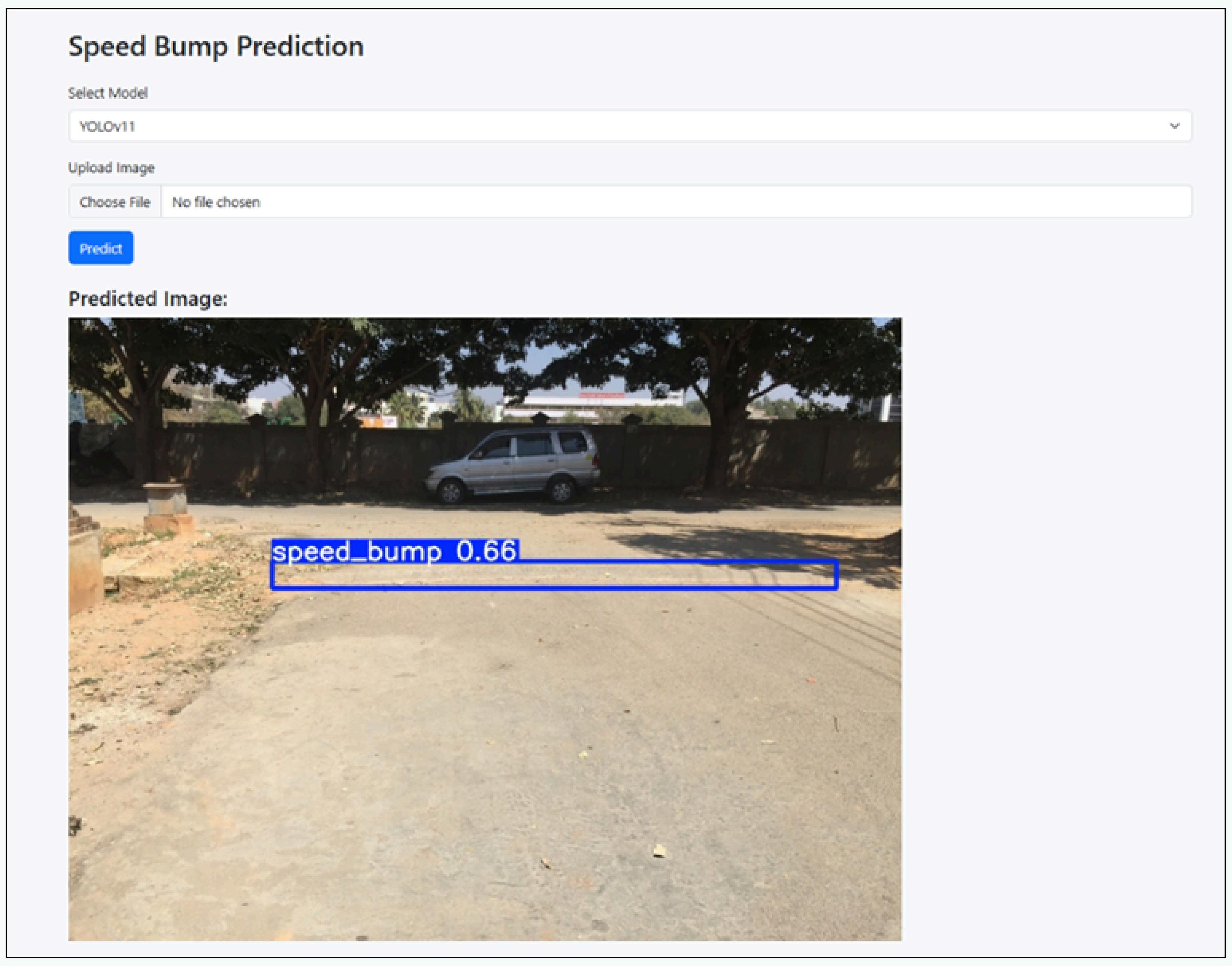


Model Evaluation

	mAP@0.5	Precision	Recall	F1-Score
Yolov11	0.9761	0.9242	0.9643	0.9643
SSD	0.7429	0.7429	0.5711	0.6458
Faster R-CNN	0.8823	0.8823	0.5674	0.6907

YOLOv11 emerged as the most effective model in this study, achieving the highest performance across all key metrics. It recorded a mean Average Precision (mAP@0.5) of 0.9761, along with precision and recall scores of 0.9642 and 0.9643, respectively. This balance resulted in a strong F1-score of 0.9643, indicating its capability to detect speed bumps both accurately and consistently.

Web Interface Implementaion



A user-friendly web-based interface was developed using a Laravel PHP framework to demonstrate the application of object detection models for identifying road bump images.

Conclusion

This project successfully demonstrates that deep learning can reliably detect road bumps under varied conditions. **YOLOv11** emerged as the optimal model due to its real-time inference and high accuracy. The practical integration via a Laravel-based web platform confirms the potential for real-world use. Future improvements may involve video-based detection, integration into in-vehicle systems and model deployment on mobile device.

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