CHAPTER VII

CONCLUSION

7.1 Summary of Findings

This research aimed to evaluate and compare the performance of YOLOv7 and YOLOv8 for road damage detection, focusing on two primary damage types: Cracks and Potholes. By utilizing three different datasets, this study examined detection accuracy, model efficiency, and real-world applicability.

The findings indicate that YOLOv8 consistently outperformed YOLOv7 across all datasets in terms of precision, recall, mean Average Precision (mAP), and inference speed. Specifically:

1. Dataset 1: YOLOv8 demonstrated a substantial improvement in detection accuracy over YOLOv7, achieving a mAP@50 of 61.4%, compared to YOLOv7's 3.04%, highlighting the model's robustness in identifying road damage under varying conditions.
2. Dataset 2: Both models performed better in this dataset than in Dataset 1. However, YOLOv8 remained superior, achieving a mAP@50 of 70.1%, while YOLOv7 achieved 43.3%, indicating YOLOv8's stronger ability to detect road damage with greater precision.
3. Dataset 3: YOLOv8 continued to surpass YOLOv7, achieving a mAP@50 of 45.2%, compared to YOLOv7's 4.5%. Notably, YOLOv8 was able to detect Potholes effectively, while YOLOv7 struggled with this class, failing to achieve any meaningful mAP scores.

Additionally, inference speed was a key factor in determining model efficiency. YOLOv8 significantly outperformed YOLOv7 in speed, achieving 13.0–16.0ms per image, compared to YOLOv7's 1.39–2.02 seconds per batch, making it far more suitable for real-time applications.

Through confidence threshold adjustments (reducing from 0.1 to 0.01 in Dataset 3 for YOLOv7), this research also highlighted the impact of confidence tuning on detection performance, showing that lowering the confidence threshold can help capture more potential detections, particularly in datasets with lower detection recall.

7.2 Conclusion

This research successfully evaluated, compared, and analyzed the effectiveness of YOLOv7 and YOLOv8 for road damage detection. The results clearly indicate that YOLOv8 is a superior model, providing higher precision, recall, and mAP scores, along with significantly faster inference times, making it a more practical and scalable solution for real-time road monitoring.

The adoption of AI-driven road damage detection systems can revolutionize infrastructure maintenance, leading to proactive repairs, cost savings, and improved road safety. By leveraging the strengths of deep learning and continuously refining model performance, future research can contribute to more accurate, efficient, and scalable road damage detection solutions.

With further enhancements in dataset diversity, model optimization, and real-world deployment, AI-powered detection models can play a critical role in developing smarter cities and enhancing global road infrastructure.