Automated Highway Pavement Management Systems: From Inspection to Maintenance

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ABSTRACT

Highway pavement assets require intensive management due to their large scale and deteriorating nature. Traditional pavement management depends on inspections using dedicated sensors and vehicles, which are both infrequent and costly. Moreover, maintenance activities face unavoidable constraints because they rely on human labor. In this study, we explore the potential of automation in two key steps over the highway pavement management cycle: inspection and maintenance. First, we propose an automated pavement monitoring system that utilizes non-dedicated vehicle sensors, including accelerometers and dashcam cameras. Pavement condition data collected by dedicated inspection vehicles are utilized as ground truth for machine learning processes. Beyond assessing current conditions, we estimate pavement deterioration models using collected panel data. These models enable service life predictions and support optimal asset management strategies to minimize expected life cycle costs over long-term planning horizons. Second, we discuss the benefits of automated pavement maintenance technologies with AI applications, in the context of life cycle analysis.

INTRODUCTION

The management of highway pavement networks poses a significant challenge due to their continuous deterioration and the high costs of conventional monitoring and maintenance methods. Traditional Pavement Management Systems (PMS) rely on periodic inspections conducted by dedicated vehicles equipped with high-resolution cameras, 3D laser scanners, and other specialized sensors [1]. Although accurate, these systems are costly and labor-intensive, resulting in infrequent assessments that delay timely maintenance and accelerate pavement degradation [1]. Such delays can increase costs and shorten pavement service life. Moreover, manual maintenance operations raise concerns about worker safety, operational efficiency, and consistency.

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To address these limitations, this study explores the potential of automation in two key steps of pavement management: inspection and maintenance. First, we propose an automated pavement management system that utilizes readily available sensors in non-dedicated vehicles—such as smartphone accelerometers and dashcam cameras—to collect vision-based distress data (e.g., cracks, potholes) and vibration-based roughness information. Ground truth data from dedicated inspection vehicles are used to train machine learning (ML) models. These models assess current pavement conditions and estimate deterioration trends using panel data, thereby enabling service life prediction and informing optimal asset management strategies aimed at minimizing long-term life cycle costs.

Second, we briefly discuss the application of automated pavement maintenance technologies, highlighting examples of advanced robotics and artificial intelligence (AI). From a life cycle analysis perspective, the integration of automation in both inspection and maintenance provides a pathway to proactive, efficient, and cost-effective pavement management.

RELATED WORK

Limitations of Conventional Pavement Management

Conventional pavement management has depended on scheduled inspections using dedicated vehicles equipped with specialized sensors. While effective, these inspections are costly and infrequent, limiting the ability to capture rapidly evolving pavement conditions. As a result, maintenance decisions are often reactive, implemented after substantial deterioration has occurred, which increases life cycle costs compared to proactive strategies. Additionally, manual maintenance processes are labor-intensive and face challenges related to safety, execution quality, and operational consistency. These limitations highlight the growing need for automated, data-driven approaches that can enhance the efficiency and responsiveness of pavement management.

Advances in Sensor-Based Inspection and Deterioration Modeling

Recent research has demonstrated the feasibility of using non-dedicated vehicle sensors to support pavement condition monitoring. Accelerometers and dashcam cameras embedded in consumer vehicles offer a scalable and low-cost alternative for collecting roughness and distress data across large networks [2]. Machine learning techniques, particularly deep learning, have shown strong performance in detecting surface defects and estimating roughness indicators such as IRI from these sensor inputs [2, 3]. Building on this, researchers are developing deterioration models based on panel data that enable long-term forecasting of pavement performance. These models are essential for estimating remaining service life and optimizing maintenance timing to reduce life cycle costs [3, 4]. The reliability of such models depends on consistent validation using ground truth data from professional inspection systems.

Automation in Maintenance and Integrated Management Systems

Alongside advances in inspection, automation in pavement maintenance is gaining momentum. Robotic systems designed for tasks such as crack sealing, pothole repair, and line marking are being developed and tested to improve safety, speed, and precision [5−7]. These systems often incorporate AI to support adaptive control and operational decision-making. The integration of automated inspection, deterioration modeling, and robotic maintenance forms the foundation of an automated pavement management system [4]. In such systems, continuous data streams feed into AI-based decision-support tools that assess current and projected pavement conditions, prioritize treatments, and coordinate robotic execution of maintenance tasks [8, 9]. This study contributes to this emerging paradigm by presenting an automated monitoring framework and discussing its potential within the context of life cycle–oriented pavement asset management.

METHODOLOGY

Data Collection

Data were collected on a 27 km expressway section between Cheongju IC and Mokcheon IC in South Korea, encompassing both asphalt and concrete pavements. A smartphone mounted in a non-dedicated vehicle recorded road surface videos, z-axis linear acceleration, vehicle speed, and GPS data (Figure 1). This methodology aligns with recent crowdsourcing-based pavement monitoring initiatives, facilitating scalable data collection under real-world driving conditions [5].

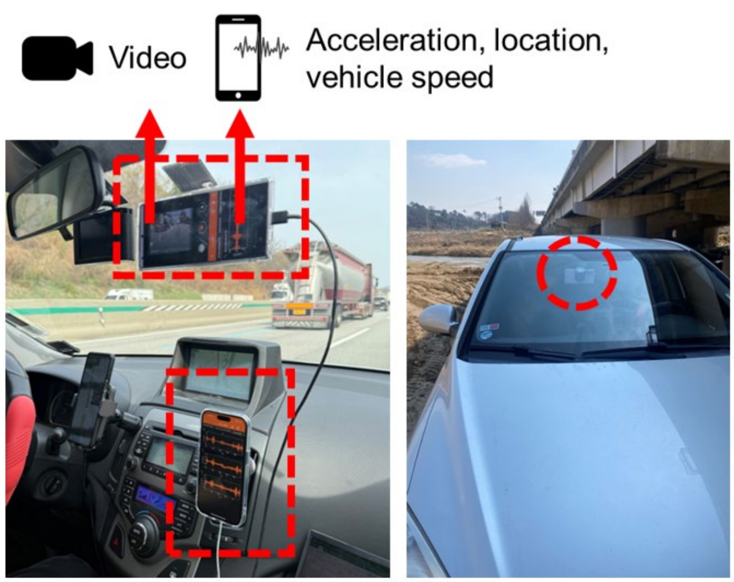

Figure 1. Experimental setup for collecting road surface video, acceleration, GPS location, and vehicle speed data using non-dedicated vehicle.

Ground Truth Data

Ground truth at 100-meter intervals, provided by the Korea Expressway Corporation, included pavement type, International Roughness Index (IRI), and Highway Pavement Condition Index (HPCI).

Sensor data collected from the non-dedicated vehicle were precisely synchronized with this official ground truth data using GPS coordinates. IRI is a widely recognized standard measure of longitudinal road profile roughness. HPCI, a composite index developed by the Korea Expressway Corporation, integrates IRI, rut depth (RD), and surface distress (SD) to provide a comprehensive assessment of pavement health. The HPCI is calculated using type-specific formulations for asphalt pavements, as shown in Eq. (1) [10]:

$$HPCI = 5 - 0.54 \times IRI^{0.8} - 0.75 \times RD^{1.2} - 0.9 \times \log(1 + SD), \qquad (1)$$

where,
IRI = International Roughness Index [m/km],
RD = Rut Depth [mm], and
SD = Surface Distress [m^2].
(The parameters multiplied by *IRI, RD*, and *SD* have specific units to ensure that all terms on the right-hand side of Eq. (1) are consistent with the units on the left-hand side.)

Model Development

For vision-based distress detection, YOLOv5x used with pre-trained weights from the RDD2022 (Road Damage Dataset), a large-scale dataset with 47,420 road surface images and over 55,000 distress instances from six countries [11]. The model was fine-tuned to identify and classify four primary distress types: longitudinal cracks, transverse cracks, alligator cracks, and potholes, achieving a mean Average Precision (mAP@0.5) of 0.647.

For vibration data analysis, the Root Mean Square (RMS) of the z-axis linear acceleration and mean speed were computed for each 100-meter road segment. These values served as effective features for directly predicting IRI and HPCI. The outputs from the vision-based distress detection (e.g., detected distress counts per captured frames of each segment) and the vibration features were subsequently combined to form multi-input feature sets. Four machine learning models—Random Forest, XGBoost, LightGBM, and a Stacking ensemble—were trained using these integrated features to predict IRI and HPCI.

RESULTS

This section details the performance of the developed automated pavement condition assessment models in predicting IRI and HPCI. The analysis compares the efficacy of different sensor input configurations (vision-only, vibration-only, and integrated vision and vibration data) and examines the influence of data volume on model accuracy. Prediction performance was evaluated using the coefficient of determination (R^2).

IRI Prediction Performance

For IRI prediction, models utilizing vibration data consistently outperformed those relying solely on vision data (Figure 2). This result aligns with the nature of IRI, which directly reflects longitudinal road roughness and correlates strongly with vehicle-induced vibrations [3]. Model performance improved as the dataset size increased, underscoring the value of continuous data accumulation for generalization.

While vision data alone offered limited predictive value for IRI, integrating vision and vibration features substantially improved accuracy. The Stacking ensemble model achieved the highest performance, demonstrating the effectiveness of multimodal sensing for robust roughness estimation.

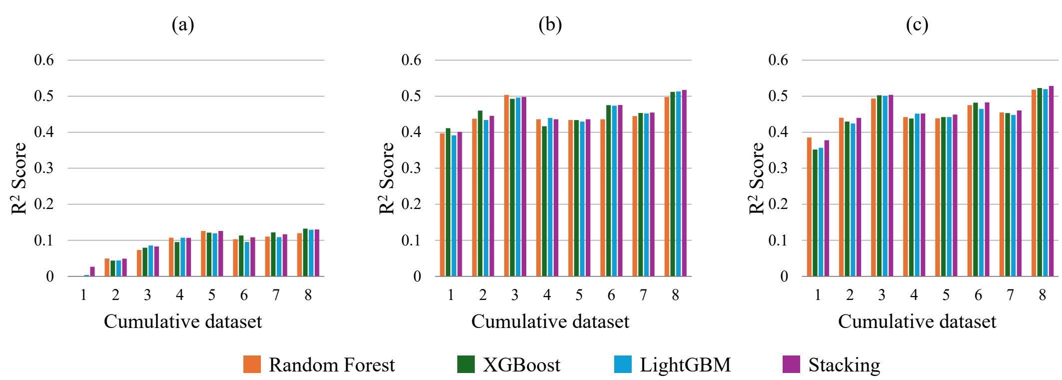

Figure 2. IRI prediction performance of four machine learning models (Random Forest, XGBoost, LightGBM, and Stacking) using (a) vision-only, (b) vibration-only, and (c) multimodal inputs.

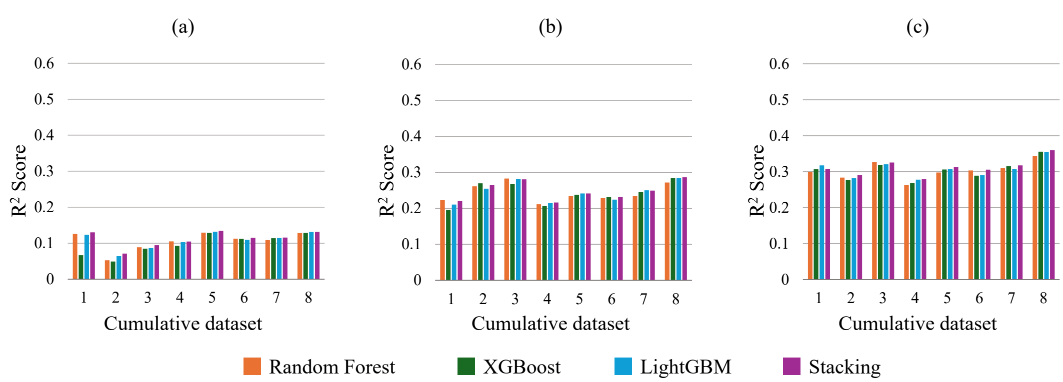

Figure 3. HPCI prediction performance of four machine learning models (Random Forest, XGBoost, LightGBM, and Stacking) using (a) vision-only, (b) vibration-only, and (c) multimodal inputs.

HPCI Prediction Performance

In HPCI prediction, the overall R^2 values were generally lower than those achieved for IRI (Figure 3). However, the contribution of vision-based features was significantly greater in this case, due to HPCI's inclusion of SD components that are visually detectable. As with IRI, multi-sensor integration improved prediction accuracy, with the Stacking model again outperforming individual models. These results confirm the effectiveness of sensor fusion for predicting composite indices and highlight the distinct role of visual information in evaluating surface-level degradation.

Implications for Deterioration Modeling and Lifecycle Optimization

Across both indices, a positive correlation between data accumulation and predictive accuracy was consistently observed. This trend supports the scalability of the proposed automated inspection framework. Longitudinal panel data derived from repeated sensing can inform deterioration modeling by capturing dynamic changes over time. Accurate forecasts of condition trajectories and service life enable highway agencies to prioritize interventions and optimize treatment timing. This predictive capability is central to minimizing lifecycle costs, transitioning from reactive to preventive maintenance planning. Ultimately, continuous sensing from non-dedicated vehicles facilitates data-driven decision-making that supports long-term asset sustainability.

DISCUSSION: AUTOMATED PAVEMENT MANAGEMENT SYSTEMS

Modernizing pavement asset management requires automating both inspection and maintenance processes. Central to this vision is the development of an "autonomous condition monitoring-based pavement management system" [4], in which data from continuous automated monitoring are used to trigger timely, precise, and robotic maintenance interventions.

Within this framework, AI functions as the system's decision-making engine. It not only processes condition data and trains deterioration models but also integrates external variables, such as traffic conditions, weather forecasts, and budget constraints, to optimize maintenance timing and resource allocation as described in Figure 4.

From a lifecycle perspective, these integrated technologies offer multi-dimensional benefits: reduced labor dependency for frequent on-site inspection, improved operational precision by more accurate understanding of current and future pavement condition, and, ultimately, prolonged pavement service life.

Automation technologies can be applied not only to inspection but also to MR&R (Maintenance, Repair, and Rehabilitation) activities. Several companies have already developed AI-robot-based pavement repair methods (e.g., Robotiz3d's ARRES PREVENT [12], RovoRoad's pothole repair robot [13]), which can enhance the economic efficiency of pavement management systems by reducing labor dependency and enabling operation during off-peak hours or in challenging environments.

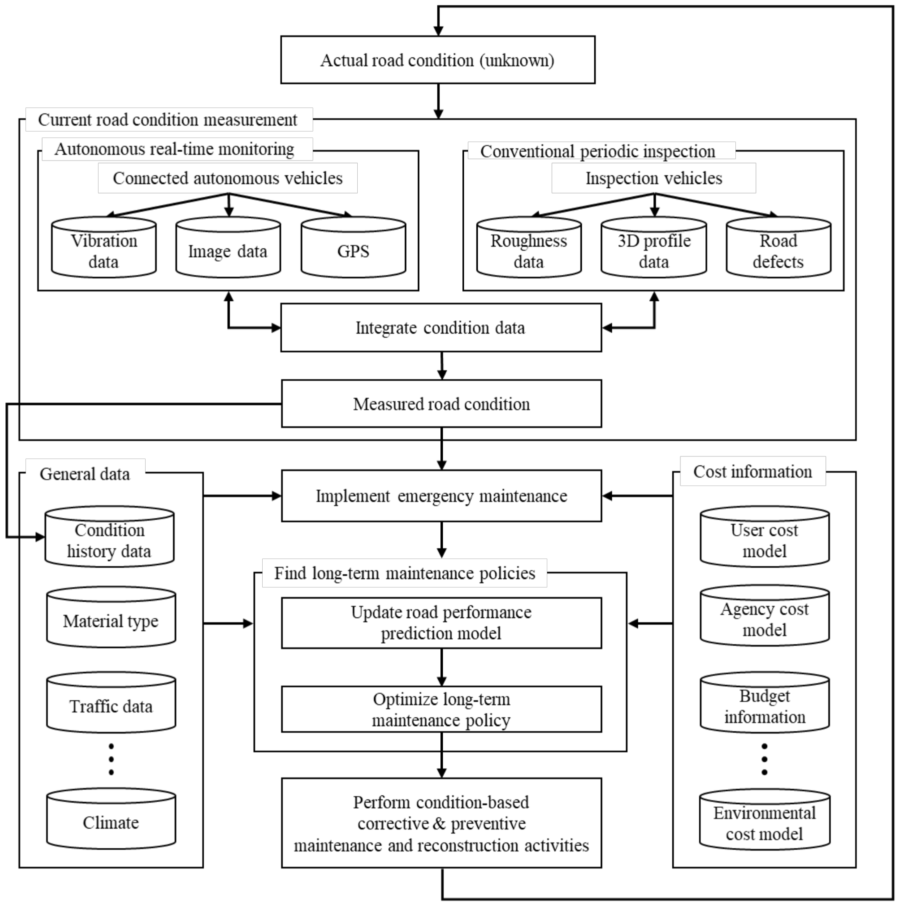

Figure 4. Concept of Automated Pavement Management Systems using real-time monitoring based on AI functions, cited from [4].

CONCLUSION

This study explored the feasibility of an autonomous pavement management system that integrates automated inspection using non-dedicated vehicle sensors with robotic maintenance technologies. By combining vision and vibration data with machine learning, the proposed framework enables continuous and scalable assessment of pavement conditions. The findings highlight that vibration features are essential for accurate IRI prediction, while vision data enhance HPCI estimation. Multimodal data fusion and increased training data further improve model robustness and reliability. AI-enabled robotic maintenance systems support precise, efficient, and safe pavement repairs, contributing to more sustainable and cost-effective asset management.

Future work will focus on strengthening model generalization, developing predictive maintenance strategies, conducting life cycle cost-benefit analyses, and exploring advanced robotic applications like crack filling and surface treatments. These advancements provide a clear pathway toward intelligent, adaptive, and fully autonomous pavement asset management. Collectively, these efforts will accelerate the transition to intelligent, adaptive, and fully autonomous pavement asset management.

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