ROAD SURFACE DIGITALIZATION: OPTIMIZING ROAD MAINTENANCE MANAGEMENT

GIẢI PHÁP SỐ HÓA BỀ MẶT ĐƯỜNG: TỐI ƯU HÓA QUẢN LÝ BẢO TRÌ ĐƯỜNG BỘ

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Abstract: The road transportation infrastructure system plays a fundamental role in socio-economic development; however, it is currently experiencing rapid deterioration due to the combined effects of climatic conditions and increasing traffic loads. This has led to the widespread occurrence of various types of pavement damage, particularly hazardous potholes. Such defects not only result in significant economic losses but also pose a high risk of traffic accidents. Meanwhile, current management and monitoring practices still rely largely on manual methods, which exhibit several limitations, including low operational efficiency, heavy dependence on human experience, and fragmented data collection. These limitations make it challenging to detect and address infrastructure failures in a timely manner.

The application of an automated detection system enables comprehensive digitization of pavement conditions through the integration of geo-tagging technology and Geographic Information Systems (GIS). The system generates a visual and objective database that allows management authorities to accurately monitor the condition of the road network in near real time without the need for direct on-site inspections. This solution contributes to transforming maintenance strategies from reactive maintenance to preventive maintenance, enabling early detection and timely repair of pavement defects at their initial stages. As a result, management agencies can optimize resource allocation, prioritize critical damaged locations, reduce maintenance costs, and extend the service life of transportation infrastructure.

Tóm tắt: Hệ thống hạ tầng giao thông đường bộ đóng vai trò nền tảng trong phát triển kinh tế - xã hội; tuy nhiên, hiện nay hệ thống này đang bị xuống cấp nhanh chóng do tác động tổng hợp của điều kiện khí hậu và tải trọng giao thông ngày càng gia tăng. Thực trạng này đã dẫn đến sự xuất hiện phổ biến của nhiều dạng hư hỏng mặt đường khác nhau, đặc biệt là các ổ gà nguy hiểm. Những hư hỏng này không chỉ gây ra những tổn thất kinh tế đáng kể mà còn tiềm ẩn nguy cơ cao gây tai nạn giao thông. Trong khi đó, các phương thức quản lý và giám sát hiện nay vẫn chủ yếu dựa vào các phương pháp thủ công, bộc lộ nhiều hạn chế như hiệu quả vận hành thấp, phụ thuộc nhiều vào kinh nghiệm của con người và dữ liệu thu thập còn rời rạc. Những hạn chế này gây khó khăn trong việc phát hiện và xử lý kịp thời các sự cố của hệ thống hạ tầng.

Việc ứng dụng hệ thống phát hiện tự động cho phép số hóa toàn diện hiện trạng mặt đường thông qua việc tích hợp công nghệ định vị địa lý (geo-tagging) và Hệ thống Thông tin Địa lý (GIS). Hệ thống tạo ra một cơ sở dữ liệu trực quan và khách quan, cho phép các cơ quan quản lý theo dõi chính xác tình trạng mạng lưới đường bộ gần như theo thời gian thực mà không cần thực hiện kiểm tra

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trực tiếp tại hiện trường. Giải pháp này góp phần chuyển đổi chiến lược bảo trì từ bảo trì phản ứng sang bảo trì phòng ngừa, cho phép phát hiện sớm và sửa chữa kịp thời các hư hỏng mặt đường ngay từ giai đoạn ban đầu. Nhờ đó, các cơ quan quản lý có thể tối ưu hóa việc phân bổ nguồn lực, ưu tiên xử lý các vị trí hư hỏng nghiêm trọng, giảm chi phí bảo trì và kéo dài tuổi thọ khai thác của hạ tầng giao thông.

Keywords: Computer Vision, Geo-tagging, Object detection, Preventive maintenance, Road maintenance.

Từ khóa: Thị giác máy tính, Gắn thẻ địa lý, Phát hiện đối tượng, Bảo trì phòng ngừa, Bảo trì đường bộ.

Received: February 15, 2026; Revised: March 24, 2026; Accepted: April 28, 2026.

1. INTRODUCTION

With a total road network length exceeding 570.000 km [3] road transportation plays a vital role in supporting economic activities and ensuring national security and defense. However, harsh tropical weather conditions combined with the increasing number of oversized and overloaded vehicles have accelerated pavement deterioration, leading to common defects such as cracking, rutting, and particularly potholes, which significantly increase traffic accident risks.

Current road maintenance practices still rely heavily on manual visual inspections conducted by field personnel. This traditional approach requires substantial human resources, produces delayed information updates, and often results in inconsistent evaluation outcomes. In addition, fragmented data collection limits effective integration into Geographic Information System (GIS) platforms, thereby reducing the efficiency of large-scale infrastructure management.

According to reports in 2024, the total maintenance demand reached approximately 11,500 billion VND, while the approved budget was limited to 3,200 billion VND, covering only about 28% of the required funding [3]. This shortage forces authorities to prioritize major damages, while early-stage defects such as potholes are frequently overlooked, resulting in higher long-term rehabilitation costs.

To address these limitations, this study proposes an automated road damage monitoring system integrating artificial intelligence, geo-tagging technology, and cloud-based databases. The system enables real-time defect detection, GPS-based location recording using the WGS84 coordinate system, and automatic hazard classification into three levels (Green, Yellow, and Red), thereby enhancing transparency, improving maintenance efficiency, and optimizing budget allocation

2. RESEARCH METHODS

This study was conducted based on synthesis and analytical methods. Relevant textbooks, scientific articles, and technical reports, as well as applicable technological models, were collected and reviewed. Based on this foundation, existing models were analyzed in terms of operational principles, advantages, and limitations to propose an appropriate reference model. The proposed model was subsequently implemented through experimental deployment using available technologies, and performance results were evaluated to assess the effectiveness of the proposed approach.

2.1. Current Road Maintenance Procedures

Currently, road maintenance activities are primarily carried out using traditional procedures, which include inspection, damage detection, reporting, and repair implementation [1][2]. Pavement inspections are typically conducted periodically or on demand by patrol and maintenance personnel through visual surveys performed directly in the field. Common pavement defects such as potholes, cracks, rutting, and surface peeling are recorded using direct observation methods and supporting photographic documentation.

After defects are identified, the collected information is compiled into written reports or paper-based forms, describing the location, severity level, and proposed repair measures. These data are subsequently submitted to management authorities for review, prioritization, and allocation of appropriate maintenance resources [1][2]. In many cases, the determination of damage severity and repair priority still depends heavily on the experience of technical personnel, which may lead to inconsistencies in the evaluation process.

Figure 1. Diagram of the current data collection process and payment of the maintenance budget for transport projects

2.2. Using geo-tagging and GIS technologies to overcome limitations of traditional inspection methods.

The pothole detection system digitizes transportation infrastructure through the integration of positioning technologies, digital mapping, and real-time data management [5]. From a technical perspective, accurate positioning capability is ensured through the Geolocator library, which enables the extraction of longitude and latitude coordinates based on the international WGS84 standard at the exact moment when the AI model detects pavement defects [5]. These data are not only stored as raw coordinates but are further transformed into geospatial data, which are directly integrated into digital maps through the flutter map framework and the OpenStreetMap platform [4], [6].

GIS-based visualization is implemented using specialized object layers such as MarkerLayer to indicate damage locations and PolylineLayer to connect survey points, enabling administrators to monitor road conditions along continuous routes rather than as isolated points [4], [6]. In particular, the status management workflow reflects an intelligent system design approach: instead of processing data directly on mobile devices, the backend server executes business logic to assess risk levels based on the density of detected potholes within a given area or frame. The road condition level is represented using three color codes like table 1.

Table 1. Regulations for marking road pavement damage levels on a GIS map

Color code	Severity level	Pavement damage severity level
Red	Dangerous	Many potholes (more than 3)
Yellow	Warning	Scattered potholes on the road surface
Green	Good	Smooth road surface, repaired

All of this information, including status color codes and repair history, is synchronized instantly via the Listeners mechanism of Cloud Firestore [7], ensuring data consistency between field surveyors and central administrators. This combination turns each report into a digital entity with full photographic evidence (stored on Cloudinary) [8], accurate geographic location, and transparent operating status, optimally supporting the preventive maintenance model [5].

2.3. Advantages Compared with Traditional Methods

Current road management and maintenance practices are facing significant challenges as traditional inspection methods reveal numerous limitations in terms of technical capability and operational efficiency. Replacing manual procedures with Artificial Intelligence (AI)-based solutions is not only a technological trend but also an urgent requirement for modernizing transportation infrastructure, offering several undeniable advantages as follows:

- Overcoming the limitations of traditional inspection processes with many disadvantages such as: high subjectivity, large errors, information delay, and fragmented data.

- Advantages of integrating AI models with mobile network systems: This approach ensures consistency and objectivity in the pavement damage identification process, enables high productivity through continuous 24/7 operation, and supports centralized data management with real-time synchronization. Consequently, administrators are provided with timely and up-to-date insights into the condition of the road network without the need for direct field inspections.

- Optimization of management workflows and budget allocation: Information generated from the AI system facilitates the transition from reactive maintenance to preventive maintenance strategies, enabling the early identification of critical damage locations and the efficient allocation of budgets to severely deteriorated areas that require urgent repair.

- Smart management support: Modern Client-Server model to optimize data collection and processing.

3. RESULTS

3.1. Smart management system

The system is designed based on a client–server architecture, ensuring a clear separation between field data acquisition and computationally intensive processing tasks performed on the server [9]. This separation enables the mobile application to function as a lightweight thin client while still leveraging the computational power of deep learning models deployed on the server [9][11]. The data acquisition and processing workflow consists of the following steps:

- Mobile Application: Acts as an intelligent data acquisition device, integrating an automatic scanning algorithm triggered based on the movement speed of the vehicle [11].

- AI Server: Responsible for performing in-depth analysis and classifying hazard levels based on the number of detected potholes within a single frame [5],[11].

- Data Transmission and Server-side Evaluation: After acquisition, image data are transmitted to the server along with corresponding GPS coordinates and timestamp information. On the server, the AI model performs pothole detection and counts the number of potholes within each frame [5],[11]. Based on these results, the system evaluates hazard levels categorized as Green, Yellow, and Red to prioritize severely damaged locations requiring immediate attention.

- Database Storage: The evaluation results are stored in the database, including captured images, GPS locations, and hazard levels associated with each detected damage point. The data are synchronized in real time, enabling historical tracking and supporting efficient maintenance management [7].

- Visualization: The processed data are visualized on a digital map platform based on GIS technology, where detected damage points are represented as geospatial objects associated with hazard-level information [4],[6],[10]. This approach enables rapid identification of high-risk areas and enhances the efficiency of monitoring road infrastructure conditions across the entire network.

- Reporting and Statistics: The system generates statistical charts illustrating damage rates over time (daily, weekly, and monthly), thereby supporting effective periodic maintenance planning and data-driven decision-making [10].

Image data associated with each detected damage point are stored in a cloud-based media storage system, ensuring reliable storage and fast retrieval of photographic evidence [8].

Figure 2. Automated assessment process

3.2. Experimental

By applying the previously developed theoretical system design framework in combination with experimental implementation using modern technologies such as Flutter, YOLOv8, and FastAPI, the proposed pothole detection system achieved promising experimental outcomes.

The dataset used in this study was developed under the name "Pothole Segmentation", which integrates data collected from multiple sources. Specifically, publicly available datasets, including the RDD2022 dataset and the Pothole-600 dataset obtained from the Kaggle platform, were combined with more than 500 real-world images captured from various road segments. Instance Segmentation techniques were employed for data annotation. Instead of using conventional rectangular bounding boxes, polygon-based labeling was applied to precisely trace the boundaries of potholes. This approach enables the model to learn the exact geometric shape and spatial characteristics of pavement damage, thereby improving detection accuracy and segmentation performance. The annotation process focused exclusively on a single object class, labeled as "pothole", with a corresponding Class ID of 0.

Following the annotation stage, data preprocessing procedures were performed, including image size normalization and orientation standardization to ensure consistency across all samples. In addition, data augmentation techniques were applied to enhance dataset diversity and simulate real-world environmental conditions. Various image filters and transformations were introduced to replicate different lighting conditions, surface textures, and environmental variations typically encountered during field data acquisition. To ensure objective model training and evaluation, the dataset was divided according to standard proportions: 70% for the Training Set, 20% for the Validation Set, and 10% for the Test Set. This structured data partitioning supports reliable performance assessment and minimizes the risk of model overfitting.

Following the training and fine-tuning processes, the YOLOv8n model achieved high detection accuracy, with an mAP@0.5 of approximately 88.1% and an average processing speed of 30–40 FPS on a GPU, effectively supporting real-time pothole recognition while minimizing false detections and false alarms under real-world operational conditions. However, missed detections still occurred, with the average recall reaching 74% and a maximum value of 87%. The missed detection rate ranged from 13% to 26%, which typically occurred in cases involving small-sized potholes, potholes located far from the input device, or those situated in low-contrast regions (e.g., poor lighting conditions or partial occlusion). To achieve a balance between Precision and Recall, an optimal confidence threshold of 0.261 was determined, resulting in an F1-score (the harmonic mean of Precision and Recall) of 0.70.

From an operational perspective, the system demonstrated reliable end-to-end interoperability among mobile devices, server modules, and cloud storage systems, with an average processing latency of 1.5–2 seconds under standard 4G network conditions. The edge-based data filtering algorithm effectively reduced redundant data by disabling image capture when vehicle speed dropped below 5 km/h, thereby optimizing storage usage and network bandwidth.

The mobile application developed using Flutter and the backend implemented with FastAPI operated stably throughout the testing phase, supporting real-time synchronization with cloud platforms such as Cloud Firestore and Cloudinary. Overall, the proposed system achieved strong performance in detection accuracy, processing efficiency, scalability, and operational stability, demonstrating its suitability for real-world deployment in intelligent road infrastructure management.

Figure 3. Storage of evaluation images on Cloudinary

4. CONCLUSION AND RECOMMENDATIONS

The proposed system contributes a practical technological solution to road maintenance operations by establishing a standardized dataset that integrates international data from the RDD2022 dataset and real-world data collected in Vietnam. The dataset was annotated using precise polygon-based labeling, enabling the model to learn the actual geometric shape of potholes rather than merely identifying bounding regions. After the fine-tuning process, the high-performance AI model achieved a reliable level of detection accuracy. These results ensure real-time pothole detection capability with high reliability while minimizing false alarms

The mobile application demonstrated stable operation and incorporated intelligent surveying algorithms based on vehicle speed. In addition, the FastAPI-based backend system, combined with Cloudinary and Firestore cloud services, enabled real-time data synchronization, allowing road condition information to be transparently managed and monitored through a digital map interface.

Despite the promising results achieved, the system still faces several challenges that require further consideration. These include dependency on Internet connectivity, the need for substantial investment in server infrastructure for large-scale data management and storage, and additional maintenance costs associated with environmental factors that may affect device durability during field deployment.

To enable large-scale real-world implementation, several potential development directions can be considered:

• Edge AI Deployment: The AI model can be converted into lightweight formats such as TFLite or ONNX to enable direct execution on mobile devices. This approach can significantly reduce network latency and allow the application to operate smoothly even in offline environments.

• Server Infrastructure Enhancement: The system infrastructure should be upgraded by deploying services on dedicated Virtual Private Servers (VPS) such as AWS or Google Compute Engine, combined with domain configuration and SSL certification to ensure high system availability and enhanced data security.

•Advanced Damage Measurement Techniques: Future research may explore the application of advanced techniques such as Stereo Vision or Depth Estimation to estimate the surface area and depth of potholes. Such data would enable automatic calculation of required repair materials, thereby supporting accurate budgeting and maintenance planning.

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