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Research Article

Designing the framework for predictive maintenance method for road surface damage management System to resilience and sustainability

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ABSTRACT

Climate change not only increases the frequency and intensity of extreme weather events but also poses significant challenges to transportation infrastructure, particularly road networks. These impacts accelerate pavement deterioration, increase uncertainty in predicting infrastructure service life, and directly affect traffic safety and operational efficiency. In response to these challenges, this study proposes an intelligent automated pavement quality management solution designed to preserve the value of road infrastructure assets throughout their operational lifecycle. The primary objective is to develop an intelligent pavement damage management framework that enhances the predictive capability and climate resilience of road transportation systems under the increasing impacts of climate change. The proposed system integrates key Industry 4.0 technologies, combining machine learning, Global Positioning System (GPS) localization, and a Decision Support System (DSS). Specifically, the framework employs the YOLOv8 model trained on a localized dataset containing more than 11,000 annotated pavement damage images collected in Vietnam, enabling real-time detection and geospatial localization of multiple pavement distress types. Experimental results demonstrate that the proposed model achieves high detection accuracy, with an mAP@0.5 exceeding 93.2%, robust recognition performance under diverse pavement conditions, and efficient inference speed of 0.91 seconds per frame. Beyond pavement damage detection, the system incorporates a predictive analytics module to estimate pavement deterioration trends and a DSS to prioritize maintenance interventions based on damage severity, associated risks, and climate change impacts. Compared with previous studies that primarily focused on damage detection or sensor-based monitoring, this research contributes a comprehensive pavement management framework that transforms conventional reactive inspection practices into proactive, predictive, and climate-adaptive infrastructure management. The proposed framework provides an effective approach to improving the sustainability, resilience, and long-term performance of road transportation infrastructure under changing climatic conditions.

Key words: Climate change, road damage detection, Intelligent management system, Resilience and Sustainability Infrastructure

INTRODUCTION

Climate change is intensifying the frequency and severity of extreme weather events, significantly threatening transportation infrastructure worldwide (Moretti & Loprencipe, 2018; Markolf et al., 2019). These disruptions, ranging from floods and storms to slow-onset phenomena such as drought and saltwater intrusion, accelerate pavement deterioration and increase risks to traffic safety. Traditional design and maintenance practices—often based on historical climatic data—are no longer sufficient to ensure resilience under rapidly changing conditions (Vajjarapu et al., 2019; Rathnayaka et al., 2023). To address these challenges, recent advances in Industry 4.0 technologies—particularly computer vision, AI-based image recognition, and GPS-enabled mapping—offer opportunities for predictive, data-driven road maintenance. Integrating these technologies enables infrastructure managers to move from reactive to proactive strategies, optimizing resource allocation and improving resilience to climate variability.

The rapid economic growth in many countries has enabled the expansion of integrated transportation infrastructure, including railways, roads, aviation, and airports. Among them, road infrastructure plays a key role in connecting economic hubs and urban centers[1]. In Vietnam, strong investment from the government has led to rapid expansion of the national road and expressway network in recent years, significantly improving transport efficiency and regional connectivity across a country with diverse geography

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stretching from North to South. However, after being put into operation, these infrastructures are increasingly exposed to multiple stressors that accelerate deterioration. For example, the Ho Chi Minh City–Trung Luong–My Thuan expressway requires an annual maintenance budget exceeding VND 95 billion to ensure serviceability and traffic safety. Climatic factors further exacerbate the situation. Vietnam's tropical monsoon climate, characterized by high temperature, humidity, and heavy rainfall, creates unfavorable conditions for asphalt pavements. Prolonged water exposure damages the asphalt binder and weakens structural layers. It is estimated that approximately 75% of pavement deterioration in Vietnam is caused by rainfall, flooding, or prolonged moisture retention. Typical signs such as longitudinal cracks, transverse cracks, and alligator cracking often emerge after only one rainy season (3–6 months) in poorly drained areas. If left untreated, these defects quickly develop into potholes, posing significant safety risks.

Another pressing challenge lies in road management practices. Despite continuous governmental efforts to improve transport efficiency, the adoption of advanced monitoring technologies remains limited at the local level. Responsibilities between agencies often overlap, and road inspections are still largely conducted manually, with paper-based reporting and long approval chains. Consequently, repair actions may be delayed for months, allowing minor damages to escalate into severe and costly failures. This critical gap motivates the present research, which aims to provide an intelligent and automated framework for damage detection and decision support in Vietnam's transportation network[2]. For instance, heavy rain can damage asphalt surfaces, while extreme heat and thermal shifts may crack concrete structures[3]. Inadequate maintenance and climate-incompatible designs have led to premature deterioration, threatening traffic safety and increasing repair costs[4]. The degradation of road networks not only reduces quality of life but also poses serious risks to public health and safety[5]. As road infrastructure typically operates for 50 to 100 years, integrating climate risk assessment into planning, design, and maintenance is crucial[6]. Proactive infrastructure management in the face of climate change is thus an urgent and global priority.

This study aims to develop a software system that integrates Industry 4.0 technologies such as artificial intelligence, computer vision, GPS, and IoT to enable intelligent and efficient road management. Specifically, the system is designed to automatically detect and geolocate pavement damages in real time based on the YOLOv6 model, while also predicting degradation trends and estimating the remaining service life (RSL) of pavement structures. In addition, a Decision Support System (DSS) is integrated to assist road authorities in optimizing resource allocation, planning maintenance activities, and enhancing infrastructure resilience to climate impacts. This approach not only improves the accuracy and speed of damage detection but also links technical data with management strategies and policies, thereby strengthening the sustainability and effectiveness of road infrastructure management.

Unlike previous studies, which focused on individual aspects such as damage detection using YOLO, SSD, or CNN, or sensor-based monitoring with LIDAR combined with GPS and 4G/5G, this study proposes a comprehensive integrated framework with three key components. First, the system applies YOLOv8, the latest version in the YOLO family, to achieve real-time pavement damage detection with higher accuracy and improved recognition of small and complex objects compared to YOLOv6/YOLOv7. Second, the study goes beyond detection by developing a predictive mechanism to forecast degradation trends and estimate the Remaining Service Life (RSL) of pavements. Finally, the system is integrated with a Decision Support System (DSS), in which detection and prediction outputs are transformed into management insights through a severity scale that incorporates climate-related risk factors. An additional highlight is that the entire software was built on a dataset collected and annotated in Vietnam, ensuring contextual relevance to local infrastructure and climatic conditions. This integration of advanced technology with a local context underscore both the novelty and the practical value of the study.

In this study, the authors developed an integrated software system for detecting and localizing road surface damage by combining computer vision, GPS-based localization, and predictive analytics. The YOLOv8 framework served as the core machine learning model, enabling real-time identification of road defects from dashboard camera footage captured by vehicles such as cars and buses[7]. GPS technology, updated in real time via 4G/5G connectivity, complemented the detection system by providing accurate geolocation of damages along road networks[8]. This integration allows road defects to be identified and mapped with high precision, offering valuable insights for transportation authorities. The novelty of this study lies in its integration of three critical components that have rarely been combined in prior research: (i) real-time AI-based road damage detection using YOLOv8, (ii) predictive analytics to estimate degradation trajectories and Remaining Service Life (RSL), and (iii) a Decision Support System (DSS) that incorporates severity scoring and climate-related risk factors. Previous studies have typically focused either on detection accuracy or on asset management models, but without linking these elements into a proactive and adaptive framework. By merging computer vision, GPS-based localization, and predictive maintenance within a unified system, this research advances beyond prior works by providing not only high detection performance but also actionable, policy-relevant recommendations for transportation agencies.

The structure of this paper is organized as follows: Section 2: Background and Related Literature; Section 3: Evaluation of Factors Influencing the Transportation Network Due to Weather and Disasters; Section 4: Presentation of the Traffic Management Software Model; Section 5: Construction of the Management, Maintenance, and Repair Process for Transportation Projects; Section 6: Results of the Models and Presentation of Software System Damage Results or Predictions; Section 7: Conclusion and Remarks.

BACKGROUND AND RELATED LITERATURE

Evolution of Deep Learning-Based Object Detection Models

Recent years have seen rapid advances in deep learning–based object detection models, particularly the YOLO (You Only Look Once) family, which has been widely applied in transportation infrastructure monitoring. Earlier versions, such as YOLOv5 and YOLOv7, demonstrated good accuracy and speed but were limited by high computational demands and reduced flexibility for complex real-world applications [9].

Released in 2023 by Ultralytics, YOLOv8 introduces several key improvements that justify its adoption in this study. It integrates multi-task capabilities—object detection, instance segmentation, and image classification—within a single framework, making it more versatile for pavement inspection [10]. The model features a user-friendly API and simplified training pipeline, enabling efficient deployment and reproducibility. Empirical results show that YOLOv8 achieves higher mean average precision (mAP) with fewer parameters than YOLOv5 and YOLOv7, offering both accuracy and computational efficiency. Architectural innovations, including a redesigned backbone, new detection head, and anchor-free loss function, further enhance convergence speed and generalization [7]. Moreover, YOLOv8 supports transfer learning with pre-trained weights and can be exported to multiple formats (e.g., ONNX), ensuring adaptability across platforms and devices.

Given these advancements, YOLOv8 provides a robust, accurate, and practical solution for pavement damage detection. Its adoption in this study aligns with the latest developments in computer vision and ensures applicability to real-world road management under climate variability.

Climate Change and Transportation Infrastructure Vulnerability

Climate change has intensified extreme weather events such as floods, droughts, heatwaves, and cyclones, severely impacting transportation systems worldwide [11]. The Asia–Pacific region is particularly vulnerable, facing risks four times higher than Africa and 25 times higher than Europe, with heavy rainfall and flooding accelerating pavement deterioration [1,2]. Building climate change adaptation (CCA) capacity has therefore become essential for safeguarding critical infrastructure and livelihoods [12]. Recent studies advocate risk-based planning, flexible infrastructure design, and early forecasting to minimize costs and losses [4,13]. However, most infrastructure systems remain designed for historical conditions [8] and unstable funding continues to constrain proactive maintenance, leading to delayed interventions and costly large-scale repairs [14]. In the coming years, transportation systems and other critical infrastructure will face increasing challenges due to limited adaptability to rapidly changing demands and climate pressures [15]. Although recent advances in transportation maintenance emphasize climate risk assessment and resilient design strategies [16], practical implementation remains limited [17]. Climate-based approaches can help identify specific damage types and support preventive planning [18], yet management frameworks have not proven effective in real-world contexts.

Traditional methods such as vision-based models [19], and modern technologies like LIDAR [20], pressure sensors [21], radar, and sonar show potential but are hindered by high costs, technical complexity, and inconsistent accuracy. Similarly, wireless sensor networks and community-based reporting [22] are widely applied but remain reactive, addressing damage only after occurrence, and therefore fail to strengthen infrastructure resilience against climate change.

AI-Based Approaches for Road Damage Detection and Identified Research Gap

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as transformative approaches for monitoring and managing road transportation systems[23]. Leveraging Industry 4.0 technologies, these methods enable real-time data analysis, damage prediction, and data-driven decision-making by integrating diverse sources of information[24]. Notably, image recognition techniques such as SSD, CNN, and advanced versions of the YOLO framework—particularly YOLOv5 and YOLOv8—have achieved strong performance in detecting pavement damage and traffic-related objects[25]. However, there remains a lack of comprehensive research that fully integrates climate factors, sensor data, and predictive capabilities into a proactive, adaptive, and sustainable intelligent traffic management system - especially in the context of urban areas within transitional economies[26]. This is the research gap that the present study aims to address, with the goal of contributing to the development of modern, flexible, and climate-resilient infrastructure management solutions.

Recent contributions have advanced AI-based approaches for road infrastructure monitoring. For example,[7] compared YOLOv5, YOLOv7, and YOLOv8 for traffic sign detection, highlighting the superior accuracy of newer YOLO variants but also their higher computational demands. Similarly,[27] demonstrated the use of YOLOv8 frameworks for pothole and speed bump detection, confirming the applicability of deep learning to roadway safety monitoring. Beyond detection,[28] and[29] emphasized the importance of integrating GPS-based localization and predictive analytics into transportation resilience planning. Despite these advances, few studies to date have proposed a unified framework that combines real-time detection, predictive maintenance scheduling, and decision support systems tailored to climate resilience. This gap underscores the novelty of the present research.

Table 1, Previous studies have acknowledged a critical gap in the literature, namely the absence of comprehensive frameworks that simultaneously integrate climate-related factors, sensor-based data, and predictive capabilities for resilient road infrastructure management.[26] emphasized that while advanced sensing and AI-based approaches have been proposed individually, they often remain fragmented and lack scalability when applied to transportation resilience. Similarly,[8] and[17] noted that existing research has either focused narrowly on damage detection or has faced significant deployment limitations, without adequately addressing climate-induced risks or enabling predictive maintenance. To bridge this gap, the present study proposes a YOLOv8-based framework that not only achieves real-time detection of road surface damages but also incorporates predictive analytics to estimate degradation trajectories and Remaining Service Life (RSL). Furthermore, the integration of a Decision Support System (DSS), which combines severity scoring with climate risk factors, enhances the capacity of transportation agencies to prioritize interventions and allocate resources effectively. Importantly, the framework is developed and validated. This summary highlights that while AI models for road damage detection are advancing, few studies integrate predictive maintenance, decision support, and climate resilience into a unified framework, which is the novelty of the present research.

PROPOSED SOLUTION FOR DEVELOPING PAVEMENT DAMAGE PREDICTION SOFTWARE

This study develops an artificial intelligence (AI)-based software system for forecasting pavement surface damage, aiming to support proactive maintenance and strengthen the climate resilience of road infrastructure. The framework comprises four components: data acquisition, preprocessing, damage detection and prediction, and decision support integration. Leveraging computer vision, machine learning, and multi-source data analytics, the system provides real-time, location-specific insights into pavement conditions. As shown in Figure 1, damage detection is performed using the YOLOv8 deep learning model, which processes dashcam video frames to identify and classify surface defects. GPS integration enables real-time geolocation and mapping of damages, while a Google-based interface supports visualization and user interaction.

System Architecture Overview

The proposed software consists of four main modules:

Data Acquisition Module: This component collects road surface images and environmental data using vehicle-mounted dash cameras and sensors (e.g., GPS, shock sensors). The use of mobile platforms allows for continuous and large-scale data collection without the need for expensive fixed infrastructure.

Preprocessing and Annotation Module: Raw images are filtered, resized, and annotated using a combination of manual labeling and semi-automated tools. Damages are classified into categories such as cracks, potholes, and surface wear, following standards like ASTM or local transportation agency guidelines.

Damage Detection and Prediction Module: This core module employs a convolutional neural network

Table 1: Summary of selected studies on road damage detection and infrastructure resilience

Author/Year	Method/Model	Key Findings	Limitation/Gap
Chapman (2007) [11]	Review on climate & transport	Highlighted vulnerability of transport to climate change	Limited adaptation strategies proposed
Radopoulou & Brilakis (2017) [8]	Automated pavement detection	Early attempt using vision-based techniques	Limited scalability and real-time capability
Arya et al. (2021) [25]	YOLOv5, CNN-based detection	Demonstrated strong performance across countries	Focused on detection only, no predictive framework
Padsumbiya et al. (2022) [17]	CNN crack detection	High detection accuracy in controlled settings	Lacked integration with asset management systems
Ortataş & Kaya (2023) [7]	YOLOv5/YOLOv7/YOLOv8 (traffic signs)	Newer YOLO versions improve detection accuracy	Computationally demanding, not optimized for road damages
Chandak et al. (2024) [27]	YOLO for pothole/speed bumps	Showed feasibility of real-time deployment	Did not address predictive maintenance or resilience

Table made by theauthors themselves, "*Source: The authors*".

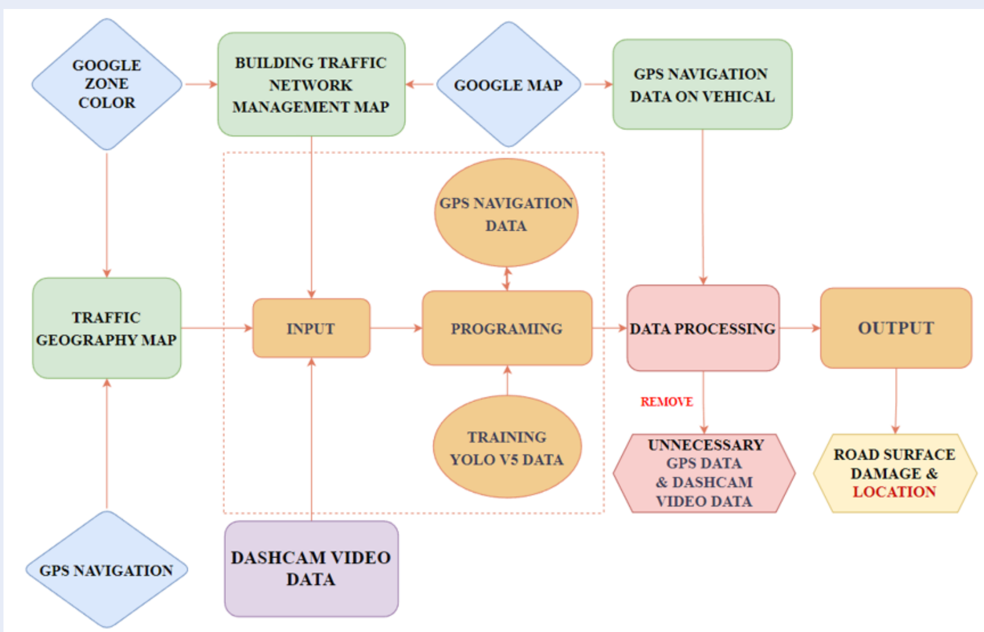

Figure 1: Data Fusion Model to build RESEARCH software Pictures made by the authors themselves, "*Source: The authors*".

(CNN)-based object detection framework, specifically leveraging YOLOv8 due to its balance between speed and accuracy. In addition to real-time detection, a predictive model is integrated using time-series data and environmental conditions to estimate the progression of surface damage over time.

Visualization and Decision Support Module: The system includes a user-friendly dashboard that displays detected and predicted damages on a GIS-based

Data Collection and Preprocessing

The dataset used to train and evaluate the proposed software consists of over 3,000 high-resolution images, extracted from video recordings captured by forward-facing dash cameras mounted on public buses. Specifically, a 70mai Dash Cam Pro Plus A500S was used, offering a resolution of 2592×1944 pixels and a frame rate of 30 frames per second (fps), suitable for capturing fine-grained pavement details in dynamic environments.

Data were collected from various inner-city bus routes in Ho Chi Minh City, Binh Duong province and Dong Nai province, which traverse different types of urban roads. The choice of using public transportation vehicles ensures consistent driving paths, diverse traffic scenarios, and broad coverage of infrastructure conditions. This approach also simulates real-world deployment settings for the system.

The captured videos encompass a variety of daylight conditions and road surface types, including asphalt, concrete, and composite pavements. From the collected footage, representative video frames were extracted at regular intervals (e.g., every 1–2 seconds) to create a balanced and diverse image dataset.

Each pavement image was subsequently reviewed and classified for visible surface distress, following two recognized standards:

- ASTM D6433 – Standard Practice for Roads and Parking Lots Pavement Condition Index (PCI) Surveys [30].
- Vietnam Road Maintenance Technical Handbook, published by the Directorate for Roads of Vietnam.

Damage types annotated include longitudinal cracks, transverse cracks, crocodile/alligator cracking, potholes, edge breaks, and rutting.

To ensure the reliability of the dataset, all images were manually annotated by a team of three trained annotators with prior experience in pavement damage assessment. A standardized labeling protocol was established, defining precise damage categories such as cracks, potholes, spalling, and rutting, along with bounding-box guidelines for each type. An initial subset of 1,000 images was independently labeled by all annotators to calibrate understanding and refine the guidelines. Inter-annotator agreement was then quantified using the mean Intersection-over-Union (mIoU), which achieved an average of 0.87 across all categories, indicating a high degree of consistency. Any discrepancies were jointly reviewed, and final annotations were consolidated through consensus. This calibration and validation process was repeated periodically during the annotation phase to minimize quality drift and to ensure that the resulting dataset provided a robust and trustworthy foundation for both training and evaluating the YOLOv8-based model.

Regarding data collection, the damage dataset was built from more than 11,000 road surface images captured by dashcams mounted on public buses operating across Ho Chi Minh City and nearby provinces. All images were manually annotated by three trained annotators following a standardized labeling protocol, with inter-annotator consistency validated using mean IoU scores. For environmental and climatic variables, we collected weather data such as rainfall and temperature from local meteorological stations operated by the Southern Regional Hydro-Meteorological Center. These variables are directly linked to pavement deterioration processes—for instance, heavy rainfall and waterlogging accelerate crack expansion and pothole formation, while temperature extremes reduce asphalt durability. Although the current experiments focused primarily on image-based detection and DSS outputs, the revised manuscript now clarifies how these climatic datasets are incorporated into the predictive module and discusses their impact on RSL estimation.

Data Preprocessing

Prior to training, the collected images underwent a series of preprocessing steps to ensure compatibility with the YOLOv8 object detection framework and to enhance model performance. These steps included:

Resizing: All images were resized to a uniform dimension of 600×600 pixels to conform with the input layer requirement of YOLOv8. This resizing ensures consistent feature scaling and computational efficiency during training.

Naming and Classification: Each image was saved using a structured naming convention, incorporating route ID, frame index, and damage type (e.g., route12_frame0105_pothole.jpg). Images were organized into folders corresponding to their damage categories to support batch processing and data augmentation tasks.

Noise Filtering and Quality Control: Images affected by excessive motion blur, poor lighting, or visual obstructions (e.g., vehicles, pedestrians) were removed to maintain data quality.

Feature Extraction and Label Formatting: Using LabelImg, bounding boxes were manually annotated for each damage instance in the YOLO format, which includes: class_id, x_center, y_center, width, height, normalized to image dimensions. These labels were saved in .txt files with the same name as their corresponding images, as required by YOLOv8.

Dataset Splitting: The full dataset was split into training (80%) and validation (20%) subsets. The split maintained a balanced representation across damage types and lighting conditions to avoid model bias.

Compatibility Conversion: The image and label sets were then structured following the YOLOv8 directory format, which includes the standard subfolders: images/train, images/val, labels/train, and labels/val.

The preprocessing pipeline optimizes the dataset for model training by reducing noise and enhancing generalization in damage detection. The training dataset consists of manually annotated images, where visible pavement defects are labeled through an object detection annotation process. This process involves both identifying and localizing damage within each image, enabling the model to learn the presence and location of defects for effective detection and localization[27]. In this study, bounding boxes are used to annotate damaged regions, each linked to a class label (e.g., crack, pothole, rutting) and encoded in YOLO format as:

- [class_id, x_center, y_center, width, height]

With all values normalized relative to the image dimensions. The annotated images and corresponding label files are visualized and verified for consistency, as shown in Figure 2. This annotated dataset forms the foundation for training the object detection model.

It is important to note that the dataset was primarily collected from urban bus routes in Ho Chi Minh City, Binh Duong, and Dong Nai. While this setting provides a realistic and consistent data source, the spatial coverage remains limited compared to the diversity of road types and climatic conditions across Vietnam and other regions. As such, the current dataset may not fully capture variations in pavement structures, lighting conditions, and environmental influences observed elsewhere, which represents a limitation to the generalizability of the trained model.

Figure 2: Bounding Box Annotation for data *Pictures made by the authors themselves, "Source: The authors".*

*YOLO V*8 module , network architecture enabling road damage detection based on machine learning training

The training of the detection model is carried out using the **YOLOv8 framework**, which consists of three key components: **Backbone**, **Neck**, and **Head**.

- **Backbone**: The backbone is responsible for feature extraction. It processes the input images through a series of convolutional layers to extract hierarchical feature maps that capture relevant spatial and semantic information. YOLOv8 leverages an enhanced backbone (e.g., CSP Darknet or Efficient Rep) for better efficiency and performance.
- **Neck**: The neck further processes the feature maps generated by the backbone. It enhances multi-scale feature fusion using structures such as the **Feature Pyramid Network (FPN)** and **Path Aggregation Network (PAN)**, which integrate information from different levels of the network. This multi-scale representation is particularly effective for detecting objects of varying sizes, such as fine cracks or large potholes.
- **Head**: The head is the final component responsible for making predictions. YOLOv8 uses a **one-stage detection** approach, where each grid cell in the feature map directly predicts bounding boxes, objectness scores, and class probabilities. This design enables high-speed The result is a trained model capable of real-time detection and classification of multiple types of pavement damage in images or video streams captured by dash cameras[31].

To ensure reproducibility and transparency, the training process and hyperparameter configurations are explicitly described. The YOLOv8 model was trained on a GPU-enabled server environment to shorten training time and handle large-scale data effectively. Hyperparameters were fine-tuned iteratively to achieve optimal performance. The learning rate was initialized at 0.01 and gradually decreased using a scheduler. The batch size ranged from 8 to 32, depending on GPU memory capacity. The number of epochs varied between 50 and 300, determined by model convergence. For baseline models, hyperparameters were optimized following their respective recommended configurations to ensure competitive performance. In cases where re-training was not feasible due to unavailable implementations, evaluation metrics were obtained from peer-reviewed literature, with clear notes provided in the corresponding table captions. This setup ensures that the reported results are both transparent and equitable, offering a robust benchmark for evaluating YOLOv8's performance on the proposed dataset.

Overview on how to implement the function of detecting road damage for research software based on the YOLO V8 model platform. To build the functionality of detecting damage, using machine learning and computer vision technologies, here is a general guide on how you can achieve this (Figure 3):

Integration of GPS Technology

To enhance the spatial intelligence and practical utility of the research software, Global Positioning System (GPS) technology is integrated as a core component of the system architecture [29]. This integration enables the precise geolocation of road surface damages and facilitates the mapping of defects onto a dynamic urban traffic network [5]. By leveraging satellite-based positioning in conjunction with Geographic Information Systems (GIS), modern GPS systems are capable of delivering real-time location data with accuracy typically within 3 meters under open-sky conditions [32]. This high level of spatial resolution supports the precise localization of road defects, allowing maintenance teams to identify and prioritize intervention areas effectively. The workflow of GPS data utilization is illustrated in Figure 4.

In the research software, GPS modules record real-time coordinates (latitude and longitude) at the moment road damage is detected by the YOLOv8 model. These geospatial data are automatically linked to detection results, enabling each defect to be geotagged and displayed on a digital map. This seamless integration of computer vision and spatial analysis supports smart infrastructure maintenance planning [28]. Beyond localization, the use of GPS reflects broader

Figure 4: GPS and GIS technologies aid in constructing the road traffic network system. *Pictures made by the authors themselves, "Source: The authors".*

Industry 4.0 trends—combining AI, IoT, and big data analytics—to enhance resilience and efficiency in transportation systems [33], In this study, the integration of GPS and GIS establishes a traffic network mapping system that underpins adaptive, real-time maintenance decisions, transforming road asset management into a data-driven and location-aware practice.

Data Integration

The integration of real-time data and internet-based information is a fundamental enabler of the intelligent functionality of the research software system. As highlighted by [34], the convergence of technologies such as GPS, computer vision, and machine learning is made possible through high-speed internet connectivity, which ensures fast and stable transmission of data across system components. However, as discussed by [35], limited or unstable connectivity can adversely impact the system's ability to accurately pinpoint damage locations, thereby reducing the reliability of maintenance decisions. Importantly, all data in the system is processed through a structured network architecture in which components are linked via a standardized Application Programming Interface (API). This API facilitates the seamless transmission of detection results, GPS coordinates, user interactions, and metadata to a centralized server [36]. The server infrastructure is responsible for:

- Storing historical data,
- Performing asynchronous analytics,
- Supporting the decision-making dashboard, and
- Enabling real-time visualization on the user interface.

This modular and scalable architecture ensures that each subsystem (data acquisition, detection, mapping, and storage) communicates efficiently while

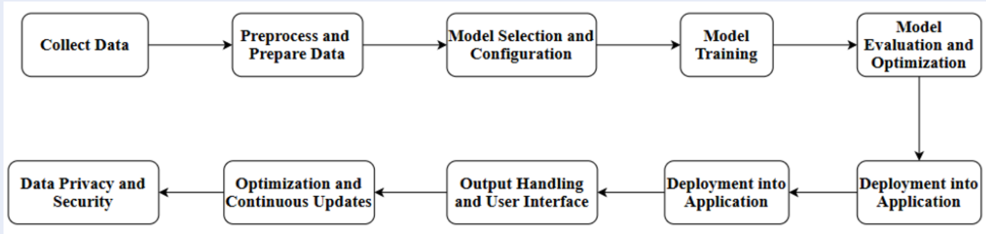

Figure 3: Process of the functionality of detecting damage *Pictures made by the authors themselves, "Source: The authors".*

maintaining system robustness and fault tolerance. Furthermore, the API-based communication model supports future expansion, allowing integration with external systems such as government maintenance databases, open-source GPS, GIS platforms, or Internet of Things (IoT) sensor networks [37]. In summary, the system architecture—anchored by stable internet connectivity and API-based server integration—forms the backbone of the proposed intelligent road damage detection platform. It enables real-time, accurate, and scalable infrastructure monitoring, paving the way for smart [38].

ESTABLISHING A PROACTIVE MANAGEMENT AND PREDICTIVE MAINTENANCE FRAMEWORK FOR ROAD SURFACE DAMAGES

The ultimate objective of this research is not only to detect and classify road surface damages in real-time but also to establish a proactive and intelligent road maintenance management framework. This framework is designed to support transportation agencies in transitioning from reactive, inspection-based methods to a data-driven, predictive, and adaptive maintenance strategy.

Framework Overview

The proposed proactive management system consists of three core components, like Figure 5:

- **Real-time data acquisition and damage detection**: via dashcam imagery and the YOLOv8 object detection model.
- **Damage classification and severity scoring**: based on standardized condition indices.
- **Predictive analytics**, leveraging historical and environmental data to estimate degradation trajectories.
- **Decision support system (DSS)**: prioritizes maintenance actions, allocates resources, and schedules maintenance.

Predictive Maintenance Scheduling

Based on the output of the detection and forecasting modules, the software estimates the Remaining Service Life (RSL) for each affected road segment. The RSL metric is computed using multi-factor analysis that considers:

- Type and severity of detected damage
- Rate of degradation over time (if time-series data are available)
- External factors such as weather conditions and traffic density

The system applies threshold-based rules to categorize maintenance urgency into three tiers:

- Routine Maintenance
- Preventive Maintenance
- Rehabilitation or Reconstruction

This approach allows authorities to prioritize interventions before failures occur, minimizing repair costs and disruptions.

Maintenance Decision Support Interface

All analysis results are visualized through an interactive user interface integrated with GIS mapping tools. This **Decision Support System (DSS)** enables infrastructure managers to:

- View real-time damaged locations
- Access historical damage records
- Simulate future deterioration scenarios
- Plan maintenance activities with budget optimization
- Generate maintenance reports with location-specific recommendations

By incorporating both technical data and climate vulnerability factors, the DSS serves as a powerful tool for climate-resilient urban transportation planning.

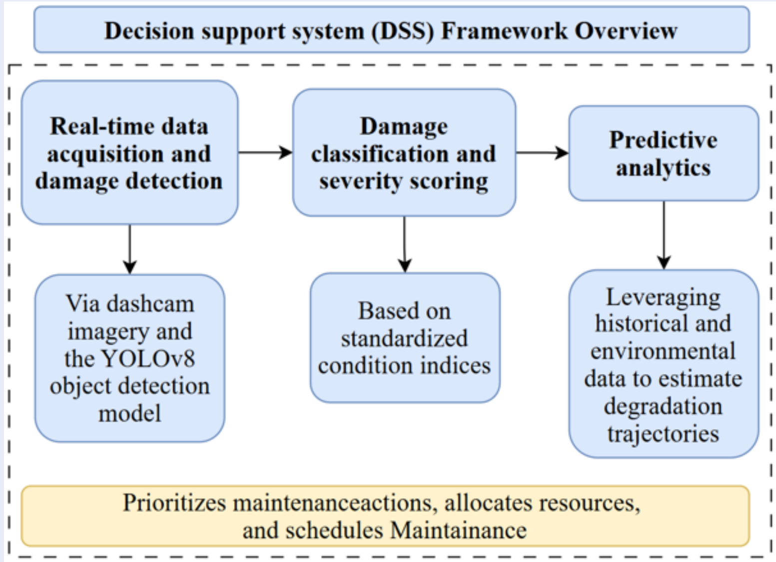

Figure 5: Illustrates the overall workflow of the proactive management system *Pictures made by the authors themselves, "Source: The authors".*

Adaptive Learning and Feedback Loop

To continuously improve accuracy and system intelligence, a feedback loop is implemented:

- Maintenance actions taken in the field are logged and synchronized with the software system.
- Newly collected image data are re-fed into the model to update training sets.
- The YOLOv8 detection model and predictive algorithm are periodically retrained to adapt to new patterns of road damage.

This adaptive mechanism ensures the long-term scalability and robustness of the management system under evolving environmental and operational conditions.

Framework for Severity Level Assessment and Decision Support System (DSS) Workflow

To enhance the precision of maintenance planning and prioritize resource allocation, this study introduces a severity assessment framework that transforms raw detection outputs into actionable insights. The framework integrates standard classification guidelines with a multi-tiered decision-making model to support a climate-resilient, data-driven maintenance strategy.

Severity Level Assessment Framework

Based on the types of road damage detected by the YOLOv8 model (e.g., potholes, cracks, rutting), the system assigns a severity level (Low, Moderate, High) to each instance using a rule-based scoring system informed by:

- **ASTM D6433**: Standard Practice for Roads and Parking Lots Pavement Condition Index (PCI) Surveys
- **Vietnam Road Maintenance Technical Manual** issued by the Directorate for Roads of Vietnam

Each damage type is evaluated based on three main factors, like as Table 2 and Table 3:

A **severity index score** is computed as follows:

$$\textbf{Severity Score} = w_1 \times T + w_1 \times G + w_1 \times D + w_1 \times C \quad (01)$$

Where:

- T = Damage type factor s
- = Geometric size factor s
- = Damage density C= Contextual factor
- w1, w2, w3, w4 = weights

Table 2: Main factors evaluate damage type, "*Source: The authors*"

Parameter	Criteria
Type of Damage	Crack, pothole, rut, depression, surface wear
Geometric Attributes	Length/width/depth of crack or pothole, area affected
Frequency/Dens	Number of damages per square meter or segment length
Contextual Importance	Road classification (arterial/collector/local), lane location, traffic load

Table made by the authors themselves, "Source: The authors".

Table 3: . Severity Score Range for Maintenance Action Decision, "*Source: The authors*"

Severity Score Range	Level	Maintenance Action
0 – 3	Low	Routine inspection/monitoring
4 – 6	Moderate	Preventive maintenance recommended
7 – 10	High	Immediate repair or reconstruction

Table made by the authors themselves, "Source: The authors".

Decision Support System (DSS) Workflow

The final stage of the framework is the integration of all analysis layers into a Decision Support System, which enables real-time decision-making for infrastructure managers. Figure 6. Workflow of the Decision Support System (DSS) for maintenance prioritization. The DSS integrates real-time damage detection from YOLOv8, severity scoring, and GPS-based mapping to generate actionable recommendations. Depending on severity thresholds, the system classifies damages into routine monitoring, preventive maintenance, or urgent repair categories, thereby guiding transportation managers in optimizing maintenance schedules and resource allocation.

- **Damage Detection**: Input image data is processed by YOLOv8 to identify and label damage.
- **Damage Classification**: Detected objects are assigned to predefined categories (e.g., pothole, crack).
- **Severity Scoring**: Each damage is scored using the above framework to determine the severity level.
- **Location Mapping**: GPS coordinates are used to locate damage on the road network map.
- **Prioritization**: Damages are sorted based on severity, road class, and traffic volume.
- **Maintenance Recommendation Engine**:

- Low severity → Routine monitoring
- Moderate severity → Scheduled maintenance
- High severity → Urgent repair

- **Visualization Interface**: All outputs are displayed on a GIS-enabled dashboard, allowing users to:

- Filter by damage type/severity/date
- Export reports and maintenance work orders
- Simulate future

This structured framework enables a systematic and transparent approach to road maintenance management, supporting both short-term responses and long-term investment planning.

In practice, this workflow allows transportation agencies to translate raw detection data into prioritized maintenance actions. For example, if more than 50% of damages along a national highway section are classified as severe, the DSS automatically recommends immediate repair within 7 days. Conversely, if minor cracks are detected on urban collector roads, the system suggests routine monitoring instead of costly interventions. This structured decision-making process ensures that limited budgets are allocated to the most critical segments, thereby enhancing both cost efficiency and resilience against climate-induced deterioration.

The Decision Support System (DSS), as the core operational interface, empowers transportation managers to make informed, data-driven decisions through intuitive visualization tools, damage heatmaps, and automated maintenance recommendations. Notably, the system shifts the paradigm from reactive to proactive and predictive maintenance, ensuring optimal resource allocation, extending infrastructure service life, and significantly improving resilience against climate-induced damage.

MODEL PERFORMANCE EVALUATION AND FORECASTED DAMAGE DETECTION RESULTS IN THE SOFTWARE SYSTEM

This section presents the evaluation of the YOLOv8-based road damage detection model, alongside the performance of the predictive maintenance module as integrated within the research software system. The results demonstrate the accuracy, reliability, and practical applicability of the proposed approach in real-world urban traffic infrastructure contexts.

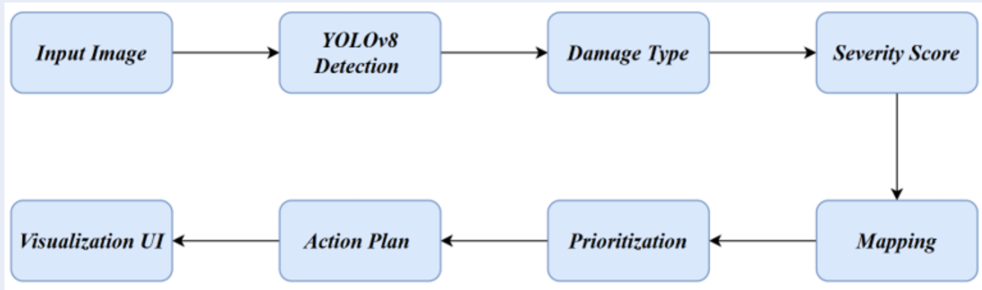

Figure 6: Workflow of the Decision Support System (DSS) for maintenance prioritization *Pictures made by the authors themselves, "Source: The authors".*

Evaluation Metrics and Experimental Setup

To quantitatively assess model performance, the following standard evaluation metrics for object detection were used:

- Precision (P): the proportion of correctly identified damage among all identified instances.
- Recall (R): the proportion of correctly identified damage among all actual damage instances.
- F1-Score: harmonic means of precision and recall.
- Mean Average Precision (mAP): measures the accuracy of object localization and classification across all categories.
- Intersection over Union (IoU): quantifies the overlap between the predicted and ground-truth bounding boxes.

The evaluation was performed on a test set of 600 annotated images, independent of the training data. Each image included one or more instances of road damage under diverse lighting and traffic conditions. To assess the RESEARCH software, a Confusion Matrix was used, comprising True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Based on the model's predictions against the ground truth, key metrics such as precision, recall, and F1-score were computed, specifically:

• True Positive (TP): The number of correct predictions of positive instances when the ground truth is also positive.

• True Negative (TN): The number of correct predictions of negative instances when the ground truth is also negative.

• False Positive (FP): The number of incorrect predictions of positive instances when the ground truth is negative.

• False Negative (FN): The number of incorrect predictions of negative instances when the ground truth is positive.

$$\bullet \text{Confusion Matrix} = \left[\frac{True\ Negative(TN)False\ Positive(FP)}{False\ Negative(FN)True\ Positive(TP)}\right] \tag{02}$$

Without:

Accuracy:

$$\bullet \text{ Accuracy} = \left[\frac{(True\ Negative\ (TN) + \ False\ Positive\ (FP)}{False\ Negative\ (FN)\quad True\ Positive\ (TP)}\right] \tag{03}$$

Precision:

$$\bullet \text{ Precision} = \left[\frac{True\ \ Positive\ (TP)}{False\ Positive\ (FP) + \ True\ Positive\ (TP)}\right] \tag{04}$$

Recall:

$$\bullet \text{ Recall} = \left[\frac{True\ \ Positive\ (TP)}{False\ Negative\ (FN)\ \ + True\ Positive\ (TP)}\right] \tag{05}$$

F1-Score:

$$\bullet \text{ F1} - \text{Score} = \left[\frac{\text{True Negative (TN)} + \text{ False Positive (FP)}}{\text{False Negative (FN)}\quad \text{True Positive (TP)}}\right] \tag{06}$$

The evaluation was conducted on a test set comprising 600 annotated images, separated from the training dataset. Each image contains one or more instances of road damage captured under various lighting and traffic conditions, the results of this research software shown in Table 4, Figures 7 and 8, *P ictures made by the TensorBoard*:

To further assess the robustness of the detection model, confidence intervals were estimated using bootstrapping on the test dataset (n = 600 images). The results indicated that Precision = 0.91 (95% CI: 0.89–0.93), Recall = 0.88 (95% CI: 0.86–0.90), and mAP@0.5 = 93.2% (95% CI: 91.8–94.5%). These narrow intervals demonstrate that the reported performance metrics are statistically stable across diverse

Table 4: the Evaluation Metrics results of this research software

Metric	YOLOv8 Performance
Precision	0.91
Recall	0.88
F1-Score	0.895
mAP@0.5	93.2%
Average IoU	78.5%

Table made by the authors themselves, "Source: The authors".

road conditions in the dataset. Although formal hypothesis testing across different environmental subsets (e.g., lighting or weather variations) was not conducted in this study, it represents an important direction for future work to validate model generalizability under broader real-world conditions.

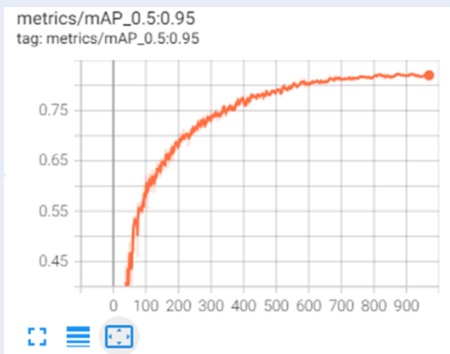

Figure 7: The mAP (0.5) results *Pictures made by the authors themselves, "Source: The authors".*

These results validate that the YOLOv8 model offers high accuracy and consistency across diverse damage types, especially in complex urban environments with occlusions and motion blur from moving vehicles.

Qualitative Detection Results

The results of research compared to a study by[39], along with the comparative outcomes of research and the model in the previous study, are presented in Table 5:

Table 4 presents a comparative evaluation of object detection models applied to road damage images. Traditional models such as Faster R-CNN achieved moderate performance, with an mAP@0.5 of 60.2% and F1-score of 60.1%. Earlier YOLO-based methods, including Yolo-LRDD, YOLOv5s, and YOLOv5m, reported similar detection accuracy

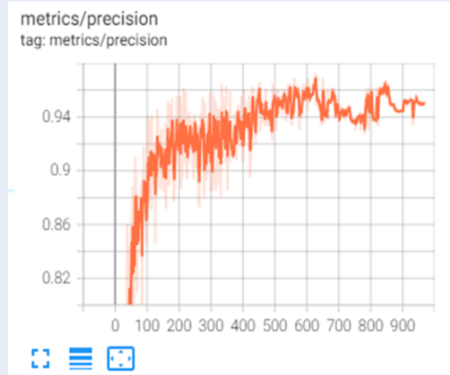

Figure 8: The precision value of this research software, *Pictures made by the authors themselves, "Source: The authors".*

(mAP@0.5 around 57%) but remained limited in recall and robustness, with F1-scores below 60%. In contrast, the proposed Research YOLOv8 model outperformed all benchmarks, achieving the highest mAP@0.5 (93.2%), mAP@0.95 (81.8%), precision (91.19%), recall (87.7%), and F1-score (89.5%). These results highlight not only the superior detection accuracy of YOLOv8 but also its balanced performance across precision and recall, confirming its suitability for real-world pavement damage detection and intelligent transportation applications.

Qualitative Detection Results

The damage detection module was deployed within the software system and tested using real-world video footage collected from public buses equipped with dash cameras. The system successfully identified and localized various road surface defects, including:

- Longitudinal and transverse cracks
- Potholes of varying depths
- Alligator cracking and edge failures
- Surface wear and depressions

Four types of damages showcase detection outputs with bounding boxes overlaid on the original road images. The bounding boxes are color-coded based on damage severity, and each detection is geo-tagged using the integrated GPS module. The system also supports multi-frame detection, ensuring consistent tracking across video frames.

Predictive Maintenance Insights

The integration of temporal detection data, combined with road usage patterns and external factors (e.g.,

Table 5: Data comparing the performance of object detection of road damage images

Method	mAP0.5(%)	mAP0.95(%)	Precision (%)	Recall (%)	F1-Score (%)
Faster R-CNN	60.2	31.8	62.7	59.3	60.1
Yolo-LRDD	57.6	30.6	59.2	58.2	58.7
YoloV5s	56.9	29.4	58.9	56.2	57.5
YoloV5m	57.3	38.9	58.5	57.3	57.8
Research YOLOv8	**93.2**	**81.8**	**91.19**	**87.7**	**89.5**

Table made by the authors themselves, "Source: The authors".

rainfall, temperature zones), enabled the predictive maintenance module to forecast potential degradation hotspots. Key outcomes include:

- Generation of priority maintenance maps highlighting zones with high-risk of degradation within the next 6 months.
- Estimation of Remaining Service Life (RSL) for critical road segments based on accumulated damage scores.
- Suggestion of optimized maintenance plans, balancing budget constraints and urgency.

Figure 9: The results identifies several images of damages *Pictures made by the RTI IMS model, "Source: The authors".*

Figure 10: The software detects alocation with damage and predicts its expansion into a serious damage in the near future, *Pictures made by the RTI IMS model, "Source:The authors".*

System responsiveness and field feedback

Preliminary pilot deployments with transportation agencies in urban areas showed positive feedback in terms of detection speed, usability, and clarity of recommendations. The average detection latency remained under 0.91 seconds per frame, enabling near-real-time processing on mid-range computing systems. In addition to overall performance metrics, a quantitative error analysis was conducted: the model exhibited a false positive rate of 6.3% and a false negative rate of 7.1%, with most errors arising in cases of small-scale cracks and faint surface distress. Figures 9 and 10 illustrate representative examples where minor damages were either missed or misclassified into adjacent categories, highlighting the practical challenges of real-world deployment. Field engineers emphasized that, despite these limitations, the software significantly improved pre-inspection efficiency and enabled proactive repair planning before visible deterioration became severe, thus reinforcing its value for preventive maintenance strategies [40].

To complement the general performance metrics, a detailed error analysis was conducted to assess the reliability of the detection results. The model achieved a false positive rate of 6.3% and a false negative rate of 7.1% across the validation dataset. Most false positives were associated with surface artifacts such as stains, patches, or road markings that visually resemble cracks or spalling, while false negatives commonly occurred in cases of small-scale or faint cracks, particularly under low-light or shadowed conditions. For instance, in one representative case (Figure 9), a hairline longitudinal crack less than 5 mm wide was missed by the model due to poor contrast against the asphalt surface. In another case (Figure 10), shallow spalling was incorrectly classified as rutting because of overlapping surface textures. These examples illustrate the inherent challenges of real-world deployment and emphasize the importance of continuous dataset enrichment and adaptive retraining. Nevertheless, field engineers noted that even with such errors, the system substantially improved pre-inspection efficiency, allowing maintenance teams to identify priority areas for repair before damages evolved into severe pavement failures.

Results of Decision Support Systems

The Decision Support System (DSS) integrated in the study plays an important role in improving the ability to analyze and make management recommendations for the authorities. Based on the data collected from the dash camera and the built-in GPS module, the system not only accurately detects and locates road surface damage, but also aggregates this information into a visual heat map, helping to prioritize areas in need of urgent maintenance. Some analytical data from the decision support system (DSS), showing the ability to assess, classify and recommend priority repair of pavement damage shown in Table 6:

Notes:

DSS recommended classifications are based on pre-set thresholds:

• Immediate maintenance if >50% of damage is serious

• Maintenance is prioritized if between 30–50%

• Periodic follow-up if between 10–30%

• No processing is required if <10%

Model Deployment and Experimental Evaluation

The proposed YOLOv8-based framework was deployed and tested on selected road segments within Ho Chi Minh City to evaluate its practical applicability under real-world conditions. In the revised experimental design, the testing phase was concentrated in District 7, Nha Be District, and Binh Chanh District, which are frequently exposed to tidal surges and waterlogging and thus represent typical climate-vulnerable urban areas. This choice allowed for a more direct assessment of how climatic factors contribute to pavement deterioration. At the same time, to ensure the robustness and generalizability of the model, the training dataset was maintained with a broader coverage, including images collected not only from Ho Chi Minh City but also from adjacent provinces such as Binh Duong and Dong Nai. This dual strategy—climate-focused testing combined with diverse training data—ensured that the model was both contextually relevant and capable of recognizing a wide variety of damage types. The evaluation results demonstrated that the model achieved high detection accuracy across multiple distress categories while maintaining stable performance in challenging conditions such as standing water, glare, and partial occlusions. These outcomes validate the framework's effectiveness as a practical tool for supporting proactive road infrastructure management in climate-affected urban environments.

The results of the analysis show that the DSS system can assess the priority of repairs based on many criteria such as: the severity of the damage, the density of traffic flow, and the frequency of damage at the same location during different inspections. From there, the software provides specific suggestions such as: "Maintenance now", "Further monitoring", or "No processing required", making it easy for managers to make decisions without having to manually process all the data. Below is a table "Severity Level Assessment Framework" showing the results of an experimental assessment of the performance of a Decision Support System (DSS), shown in Table 7:

The severity levels presented in Table 6 (low, moderate, and high) were determined based on the composite DSS severity score, which integrates four main parameters: (i) type of damage (e.g., crack, pothole, rutting, surface wear), (ii) geometric attributes (length, width, depth, or affected area), (iii) density or frequency of occurrence, and (iv) contextual importance of the road segment (e.g., arterial, collector, or local road). A weighted scoring formula was applied to these parameters, producing a severity index ranging from 0 to 10. Scores from 0–3 were classified as low impact, indicating minor damages requiring routine monitoring. Scores from 4–6 were classified as moderate impact, suggesting preventive maintenance actions. Scores from 7–10 were classified as high impact, requiring urgent repair or reconstruction. At the current stage, these thresholds were applied uniformly across all road types to validate the feasibility of the proposed framework. Future work will focus on refining and differentiating these thresholds for specific road classifications to enhance practical applicability.

A highlight of the system is the ability to update data in real time, thereby supporting quick decision-making, especially in emergency situations after natural disasters such as heavy rain, floods, or landslides. The system also allows customization of decision-making criteria according to local conditions or different maintenance objectives, ensuring flexibility in management.

CONCLUSION AND COMMENTS

Conclusion

Liu and Ke[41] reported that the challenge of climate change is one of the greatest difficulties facing humanity as a whole. Collaboratively working to protect the environment and cope with climate change is a task

Table 6: **Detection Results and Recommendations from the DSS System**

Survey Area	Number of Detected Damages	Rate of Severe Damage (%)	DSS Maintenance Recommendation	Additional Notes
National Route 1 - A Section	58	43.1%	Prioritize maintenance within 7 days	High volume of heavy vehicles
Urban Road - City B	34	17.6%	Weekly condition monitoring	Mostly minor cracks and light rutting
National Route 13 - C Section	92	56.5%	Immediate maintenance required	Large potholes and widespread cracking
Rural Road - District D	19	5.3%	No immediate action needed	Pavement conditions remain within safe range
Expressway - Section E	76	38.2%	Prioritize in quarterly plan	Affected by weather and localized subsidence

Table made by the authors themselves, "Source: The authors"

Table 7: **Severity Level Assessment Framework – DSS Evaluation Results**

No.	Location Segment	Damage Type (T)	Geometric Size (G)	Density (D)	Context (C)	Severity Score	Severity Level	DSS Maintenance Suggestion
1	QL1. Km25-Km26	2 (Crack)	2 (Medium)	1 (Low)	2 (Urban)	2.0	Low	Routine inspection
2	QL13 – Km40-Km42	3 (Pothole)	3 (Large)	3 (High)	3 (Highway)	9.0	High	Immediate repair
3	DT741 – Km10-Km11	2 (Rut)	3 (Large)	2 (Medium)	2 (Urban)	6.5	Moderate	Preventive maintenance
4	BD city	1 (Surface wear)	1 (Small)	1 (Low)	1 (Local)	1.5	Low	Routine inspection
5	QL22 – Km15-Km16	3 (Pothole)	2 (Medium)	3 (High)	2 (Collector)	8.0	High	Immediate repair or reconstruction
6	CT city	1 (Crack)	2 (Medium)	2 (Medium)	3 (High load)	5.5	Moderate	Preventive maintenance recommended

Table made by the authors themselves, "Source: The authors"

not only for the present generation but also for the future of humankind [4]. Present-day humans need to take responsibility for the significant consequences of past impacts on nature and simultaneously plan to live in harmony with nature in the future [42]. This role and responsibility must be collectively fulfilled by every individual or organization to contribute to the protection of our unique living environment [2]. In terms of transportation infrastructure, it is a product built to meet almost all components within society [43]. Transportation plays a crucial role as the lifeblood for every national economy [44]. However, most transportation infrastructures built to date have had to face challenges primarily from natural elements such as sun, wind, rain, and humidity. The challenges from nature are becoming more severe for transportation infrastructure as the impacts from natural disasters are on the rise due to climate change [19]. This study aims to minimize the impact of climate change and enhance the resilience of the transportation road system against the risks posed by climate change.

The evaluation confirms that integrating YOLOv8 into the research software delivers high accuracy (mAP >93%) and consistent performance under real-world conditions, making it both robust and applicable for urban infrastructure management. Beyond detection, the predictive maintenance module enhances value by assessing severity, forecasting degradation, and recommending timely interventions, while GPS-based geolocation and real-time processing strengthen proactive decision-making.

These findings highlight the potential of AI-driven tools to shift road maintenance from reactive to predictive, offering a scalable, efficient, and climate-resilient solution, particularly relevant to transitional economies. The system contributes to resilience against climate change, traffic safety, and optimized maintenance costs. Moreover, it establishes a foundation for future applications of machine learning infrastructure management, with further improvements expected through faster computation, higher accuracy, and larger training datasets.

Limitations

Despite promising results, this study faces several practical limitations. First, the dataset was primarily collected from urban bus routes in southern Vietnam, which constrains spatial diversity and may limit the generalizability of the model to different road conditions and climates. Second, the system currently relies on surface-level imaging and a limited set of defect categories, excluding subsurface or drainage-related failures. Third, operational constraints such as GPS accuracy, internet connectivity, and adverse weather (e.g., heavy rain, fog, or nighttime) may reduce detection and localization reliability. Finally, real-time field validation under live traffic conditions remains limited, and large-scale deployment tests are required to assess long-term stability.

Future Research Directions

To overcome these limitations, future work should expand datasets across diverse geographic regions and road environments, while integrating additional sensing modalities such as LiDAR, infrared cameras, or accelerometers to capture complex defects. Edge AI deployment and model optimization (e.g., pruning, quantization, lightweight YOLO variants) are also recommended to enable real-time processing on resource-constrained devices. Furthermore, linking the proposed framework with pavement management systems and policy-oriented studies would facilitate practical adoption, bridging the gap between technical innovation and institutional implementation in transitional economies.

Policy and Practical Implications

The proposed framework provides actionable insights for transportation agencies, particularly in transitional economies where financial and institutional constraints are significant. From a practical perspective, the system can leverage existing public transport fleets (e.g., buses equipped with low-cost dash cameras) to collect continuous road condition data without requiring large upfront investments in specialized survey vehicles. The integration with existing 4G/5G networks further reduces deployment costs, enabling scalable monitoring in urban areas.

At the policy level, adoption requires alignment with current road asset management practices and the establishment of data-sharing protocols between government agencies and technology providers. Budgetary barriers can be mitigated through phased implementation—starting with pilot corridors in major cities before scaling nationwide—and through public–private partnerships that distribute both costs and technical expertise. Importantly, the system's decision support capabilities allow agencies to justify maintenance priorities with transparent, data-driven evidence, which can improve institutional accountability and attract policy support for climate-resilient infrastructure investment.

CATEGORIES OF ACRONYMS

ITS:Intelligent Transportation Systems

DSS: Decision suport system

R&D: Research and development

AI: Artificial Intelligence

ML: Machine Learning

GPS: Global Positioning System

IoT: Internet of Things

YOLO: You Only Look Once

STATEMENTS & DECLARATIONS

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All two authors wrote, prepared and reviewed the manuscript.

The following data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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Bài nghiên cứu

Thiết kế khung cho phương pháp bảo trì dự đoán cho hệ thống quản lý hư hỏng mặt đường đến khả năng phục hồi và bền vững

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TÓM TẮT

Biến đổi khí hậu không chỉ làm gia tăng tần suất và cường độ của các hiện tượng thời tiết cực đoan mà còn đặt ra những thách thức nghiêm trọng đối với cơ sở hạ tầng giao thông, đặc biệt là mạng lưới đường bộ. Các tác động này đẩy nhanh quá trình xuống cấp của mặt đường, làm gia tăng mức độ không chắc chắn trong dự báo tuổi thọ công trình và ảnh hưởng trực tiếp đến an toàn cũng như hiệu quả khai thác giao thông. Trước bối cảnh đó, nghiên cứu này đề xuất một giải pháp tự động hóa công tác quản lý chất lượng mặt đường thông minh nhằm duy trì giá trị tài sản hạ tầng giao thông trong suốt vòng đời vận hành và khai thác. Mục tiêu của nghiên cứu là phát triển một khuôn khổ quản lý hư hỏng mặt đường thông minh có khả năng nâng cao năng lực dự báo và thích ứng của hệ thống giao thông đường bộ trước các tác động của biến đổi khí hậu. Hệ thống được đề xuất tích hợp các công nghệ của cuộc Cách mạng Công nghiệp 4.0, kết hợp công nghệ máy học, định vị GPS và hệ thống hỗ trợ ra quyết định (Decision Support System – DSS). Cụ thể, mô hình sử dụng mô hình YOLOv8 được huấn luyện trên bộ dữ liệu bản địa gồm hơn 11.000 hình ảnh hư hỏng mặt đường đã được gán nhãn, thu thập tại Việt Nam, cho phép phát hiện và định vị địa lý theo thời gian thực nhiều dạng hư hỏng khác nhau. Kết quả thực nghiệm cho thấy hệ thống đạt độ chính xác phát hiện cao (mAP@0.5 đạt trên 93,2%), khả năng nhận dạng ổn định trong nhiều điều kiện mặt đường khác nhau và tốc độ suy luận hiệu quả (0,91 giây/khung hình). Bên cạnh chức năng phát hiện hư hỏng, hệ thống còn tích hợp mô hình phân tích dự báo nhằm ước tính xu hướng suy giảm chất lượng mặt đường và DSS để ưu tiên các phương án bảo trì dựa trên mức độ hư hỏng, rủi ro và tác động của biến đổi khí hậu. So với các nghiên cứu trước đây chủ yếu tập trung vào phát hiện hư hỏng hoặc giám sát dựa trên cảm biến, nghiên cứu này đóng góp một khuôn khổ quản lý toàn diện, chuyển đổi phương thức quản lý từ kiểm tra mang tính phản ứng sang quản lý chủ động, dự báo và thích ứng với biến đổi khí hậu, qua đó góp phần nâng cao tính bền vững và khả năng chống chịu của hạ tầng giao thông đường bộ.

Từ khoá: Biến đổi khí hậu, phát hiện hư hỏng đường bộ, hệ thống quản lý thông minh, hạ tầng bền vững và kiên cường

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