AI Powered Road Damage Auditing and GPS Reporting System

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I. Abstract

Infrastructure Road infrastructure is very crucial in road safety and economic development [10]. However, road surfaces wear out with time because of traffic, environmental factors and deteriorated materials creating defects like potholes, etc [2], [8]. Normal road inspection. Surveys and complaints of the people are done manually, and they are depended on to identify the methods. are labor intensive, time-consuming and human error prone [10]. New developments in artificial intelligence and computer vision. Automated road damage detection has been possible using [1]–[3]; current systems pay attention only to the accuracy of defect detection and lack introduced geospatial reporting and severity analysis [6]. This paper is an AI-based road damage auditing and GPS. combines road damage based on deep learning-based reporting system. identification using real-time geolocation through GPS and severity. assessment. The suggested system identifies the abnormalities in the roads, sets geographic coordinates, and maps the locations of damage. on electronic maps to assist in the process of effective municipal maintenance. intelligent city facility management [6], [10].

II. IEEE Keywords

Road Damage Detection, Computer Vision, Deep Learning, Severity Estimation, GPS Mapping, Smart Cities

III. Introduction

The modern transport systems are based on the road infrastructure which is crucial to provide safe mobility and economic development [10]. Road surfaces continue to experience work and wear of their mechanical structure, environmental situations, and material breakdown as road networks keep on growing and traffic moves on the road increasing [2]. In the long run, this leads to surface defects like potholes and cracks, which affect the driving comfort negatively, raise the cost of car maintenance and are life threatening to the road users [11]. The monitoring of the road conditions in most areas is still done through the traditional means, which rely on the manual inspection periodically or on the opinions of the people. Although these methods are a decades old, they are limited in a number of ways. Manual inspections are expensive in terms of human resource and financial costs and complaint-based reporting is frequently late and intermittent. Consequently, a large number of road flaws are not identified or are only treated [10].

IV. Problem Statement

Although automated road damage detection has made a significant step, most of the current systems can only detect the occurrence of defects and eliminate their geographic location [1], [3]. This information is valuable, but it is not all that road maintenance authorities would need in their practical work. In practice, not every pothole or crack will be equally dangerous, and all the defects that have been identified should be treated in the same way, which complicates organizing adequate maintenance efforts. The majority of existing strategies fail to measure the extent of damage to roads and the mechanisms to prioritize the urgent repair [1], [3]. Consequently, the decision-makers do not have the required insights to decide which road segments should be dealt with as soon as possible and which could be maintained in the future. This weakness diminishes the value of automated detection systems in operation and restricts their use in managing large-scale infrastructure. Moreover, most of the solutions available are isolated detection models but not integrated systems, and they do not provide much assistance in real-time monitoring and decision-making [6]. Thus, there is apparent necessity to have an automated and scalable road damage auditing system with real-time detection and GPS-enabled reporting and analysis of severity. Such system would convert raw detection outputs into useful data, and allow proactive road maintenance, effective resource allocation and better transportation safety [10].

Besides detection, other studies have incorporated the use of GPS tagging to identify detected road defects with geographic locations [6], [10]. Although this is an enhancement of spatial understanding, most of the available solutions restrict their roles to simple location identification or visualization. Severity estimation and spatial prioritization of road damage are the critical aspects most of the time ignored and this decreases the utility of these systems in the planning and decision-making of maintenance. Besides, much of the existing literature has been dedicated to the model performance as opposed to full system implementation and thus, the solutions are not scalable and ready to be implemented in practice [3], [6]. These constraints indicate how a shared road damage auditing framework with enhanced capability in detecting and reporting as well as actionable insights is required as an end-to-end framework.

at a very advanced stage thus, exposing people to a greater risk of accidents and destruction of infrastructure [11]. Recent advancements in artificial intelligence and computer vision have offered new possibilities of automation of road condition assessment. The road damage detection systems based on vision can examine the images captured by the vehicle-mounted or mobile cameras and determine the surface abnormalities with a great level of accuracy [1], [3], [4]. Although this has been achieved, majority of the solutions that are available have mainly been created to indicate the existence of road defects but do not offer information on their relative effect or urgency [6]. These systems cannot be very useful in the practical road maintenance planning because of the lack of severity assessment. To overcome these issues, the proposed research suggests a unified AI-driven road damage auditing system as a combination of automated identification and GPS-enabled reporting, as well as severity-conscious analysis. The proposed approach can help to proactively monitor infrastructure conditions and implement more effective road maintenance policies in intelligent transportation infrastructure by turning visual road data into place-specific and decision-oriented information [10].

V. Objectives

1) To construct a kind of automated and intelligent road damage auditing scheme that will allow initiating continuous monitoring of the state of the road surface of urban and semi-urban transportation systems [10].
2) The purpose of the research is to implement computer vision methods based on deep learning to detect road surface defects, such as potholes and cracks, with high accuracy and in real-time and under challenging conditions related to the environment and traffic conditions [1], [3]–[5].
3) The maintenance prioritization should be supported to design a severity-aware road damage analysis mechanism to assess the comparative impact of detected defects based on visual characteristics and spatial distribution [1], [3].
4) To combine GPS-based geo-referencing with the information on the road damage that has been identified to be precisely localized and spatially analysed on the road defects [6], [10].
5) To deliver map-driven visualization of identified damages and severity levels of the roads to assist data-based decision-making by the transportation authorities and municipal agencies [6], [10].
6) To ensure the elimination of the manual inspection and complaint based reporting, which further depends on manual feedback, by providing automated, scalable, and cost effective road condition monitoring [10].
7) To illustrate the relevance of the proposed system as a decision-support system in the management of the transportation infrastructure in smart cities [10].

VI. Research Gap

1) The current road damage detection systems mostly concentrate on the detection of the surface defects and little attention is paid to the severity and urgent maintenance [1], [3].
2) Location tagging based on GPS is frequently merely employed to provide simple visualization, and not to assist with the prioritization of all the roads and the decision-making process [6], [10].
3) The existing solutions are more model-oriented and fail to offer an end-to-end solution to include detection, severity-conscious analysis, and geospatial reporting [6].
4) No scalable and practical systems exist that can convert the results of the detection into practical information that can be used in managing the transportation infrastructure in real-life situations [10].

VII. Proposed System

The suggested system is developed as an end-to-end solution that will automate the process of monitoring and reporting the road damages [10]. It combines several functional blocks that operate in order to convert unstructured road images into useful and location-related data to maintain infrastructure. The general structure comprises of data capture, preprocessing of images, damage detection, damage severity estimation, GPS, and reporting.

VIII. Literature Survey

Initial studies of road damage auditing heavily depends on the traditional image processing methods, including edge detection, thresholding, and simple texture analysis. Despite the fact that these approaches provided a preliminary resolution to detecting surface abnormalities, their functionality lacked in practical circumstances. The lighting, shadows, weather conditions and the texture at the road could be different and. using these methods led to uneven results thus could not be used to constantly monitor the road [8]. Recent studies have been directed toward data-driven models of road damage detection with the development of machine learning and deep learning. Convolutional neural networks and real-time object detection models especially YOLO-based models have shown better accuracy and efficiency in detecting potholes and cracks on road images [1], [3], [4], [7]. The models are more appropriate to practical use as they can process and fit quicker and adapt more effectively to the dynamic visual patterns.

A. Data Acquisition

The images of the road surface are captured by cameras on cars or regular mobile devices on the way of normal traveling [1], [6]. The given method allows gathering information constantly and without interrupting the data collection process, without using any specialized equipment. The pictures that are captured depict real world driving conditions and are the major input to the system.

B. Image Preprocessing

In order to increase the odds of finding an object, the obtained images are processed by a sequence of preprocessing operations. Image Scaling, noise reduction, and contrast enhancement are just some of the techniques used by OpenCV to normalize the input data and minimize the effect of lighting, shadows, and noise in the environment [8], [11].

IX. Severity Estimation Model

The weighted scoring mechanism which is a combination of visual and spatial features is used to compute the levels of severity [1], [3].

A. Damage Detection

The images preprocessed are processed through an object detection model based on deep learning and is able to detect typical defects in the road surface, including potholes and cracks [1], [3], [4]. The model works in real time and produces bounding boxes of detected damages, which allows effectively and correctly localizing road defects.

B. Severity Score Formulation

$$S = w_1 A + w_2 L + w_3 D + w_4 F \tag{1}$$

C. Severity Classification

In which, the abbreviations A, L, D, F, and w_i denote, respectively, normalized damage area, crack length, or size of potholes, density of damage per road section, detection frequency and the sum of w_i equals one.

D. Severity Estimation

To determine the severity levels of each road defect, the visual and spatial features of the detection output are analyzed to estimate the severity [1], [3]. The computations of a severity measure based on features like the relative size of the damage detected and its spatial distribution enable the system to differentiate between small and critical defects of the road.

TABLE I
Severity Level Classification

Severity Level	Score Range	Action Required
Low	0.00–0.25	Monitor
Moderate	0.26–0.50	Schedule Repair
High	0.51–0.75	Urgent Repair
Critical	0.76–1.00	Immediate Action

E. GPS Integration and Reporting

Each of the identified road defects is related to geographic coordinates determined via GPS so that this data can be used in making practical decisions [6], [10]. The information on geo-tagged damage, the severity, which is estimated, is displayed on the digital maps in a form of intuitive visualizations. This will help road maintenance authorities monitor the conditions of roads, find out the areas that are at high risks and give priority to the activities undertaken to maintain the roads.

Algorithm 1 AI Powered Road Damage Auditing

```
Capture road surface image
Preprocess image
Detect road damage using deep learning model
if damage detected then
    Extract visual features
    Compute severity score
    Acquire GPS coordinates
    Store damage details
end if
Visualize results on digital map
```

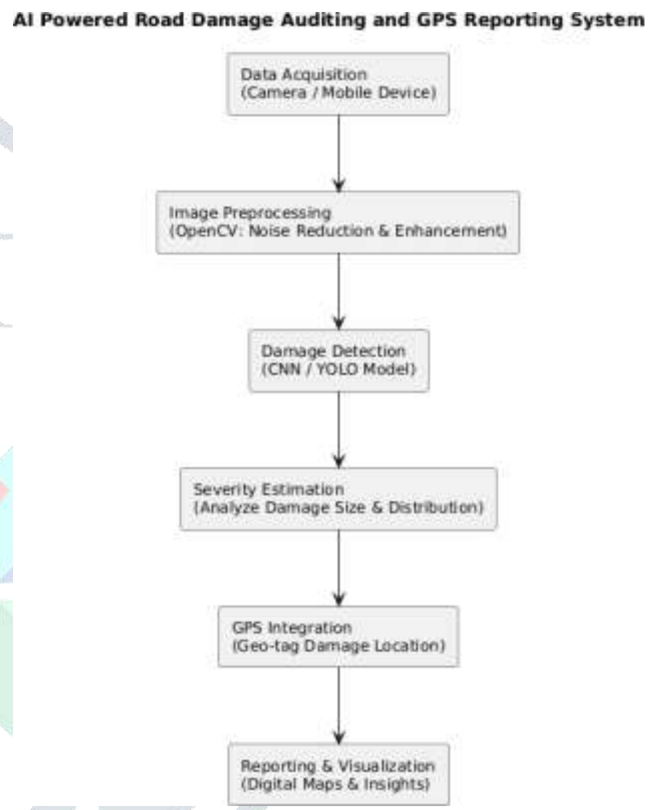

Fig. 1. Proposed system architecture of the AI powered road damage auditing and GPS reporting system

X. Results and Performance Evaluation

The standard object detection metrics such as Precision, Recall, F1-score, and average mean Average Precision (mAP) were used to evaluate the system [1], [3], [4]. The designed model was found to be performing strongly in the different lighting and road environments [7], [14].

TABLE II
DETECTION PERFORMANCE METRICS

Metric	Precision	Recall	F1-score
Potholes	0.91	0.88	0.89
Cracks	0.89	0.86	0.87

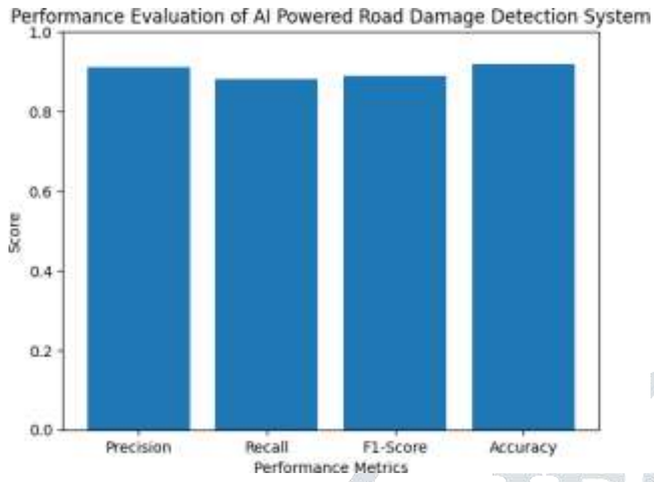

Fig. 2. Performance evaluation of the proposed AI-powered road damage auditing system

A. Detection Performance Metrics

B. Results Graphs

C. Confusion Matrix

XI. GOOGLE MAPS SEVERITY VISUALIZATION

Road damages detected are represented in Google Maps by colored markers of different severity levels [6], [10]. Green indicates low severity, yellow indicates moderate severity, orange indicates high severity, and red indicates critical damage areas.

XII. CONCLUSION

In this paper, we have described an AI Powered Road Damage Auditing and GPS Reporting System that combines the deep learning-driven detectors with the severity prediction and geospatial reporting [1], [3], [6], [10]. The suggested framework transforms uncoded detections into actionable informational nuggets, which allows proactive maintenance of roads and smart infrastructure management of a city.

SCOPUS / IEEE CONFERENCE ABSTRACT VERSION

A proposal is the automated road damage auditing system that incorporates computer vision of deep learning and severity reporting with GPS [1], [3], [6]. The system is able to monitor real time activities and identify potholes and cracks, calculate severity in both visual and spatial features and display the place of damage on digital maps. Both experimental outcomes prove the correct detection, good prioritization, and appropriateness to smart city implementation.

TABLE III
CONFUSION MATRIX

	Predicted Damage	Predicted No Damage
Actual Damage	TP	FN
Actual No Damage	FP	TN

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