

Pothoscape: Survey of Automated Pothole Detection and Hazard Warning

Master. Uttkarsh Hiray¹, Master. Suhas Satdive², Ms. Mansvi Sonje³,
Ms. Tanmayee Patil⁴, Mrs. Pramila S. Gaidhani⁵

Students, Computer Engineering¹⁻⁴

Guide, Sr. Lecturer, Computer Engineering⁵

Guru Gobind Singh Polytechnic, Nashik, India

Abstract: Potholes and other road-surface defects are persistent transportation-safety and infrastructure-maintenance problems. Conventional inspection methods can be labour-intensive, periodic and expensive, while isolated sensing approaches may detect a road anomaly without providing sufficient visual context, accurate location or timely warning to road users. This literature survey reviews research on automated pothole and road-damage detection using computer vision, deep learning, smartphone sensors, GPS, crowdsensing and integrated real-time systems. The reviewed studies show a progression from vibration-based and sensor-based detection toward image-based object detection and, more recently, systems that combine detection with geographic mapping and driver-oriented warning. The literature also indicates that model accuracy depends on dataset diversity, environmental conditions, camera quality and deployment constraints. Smartphone-based approaches offer low-cost sensing, whereas deep-learning approaches provide stronger visual identification but can require greater computational resources and representative training data. Based on the comparison, a practical gap remains in integrating low-cost automatic detection, location tagging, continuous road-condition mapping and timely hazard warning within one deployable workflow. The survey therefore establishes the research basis for Pothoscape, a proposed road intelligence system intended to detect potholes automatically, warn approaching users and maintain a continuously updated road-condition database for future maintenance support.

Keywords: Pothole Pothoscape, Deep Computer Vision, Road Damage Detection, Detection, Road Crowdsensing, Smartphone Sensors, GIS Mapping, GPS, YOLO, Learning, Road Safety Edge Computing, Real-Time Hazard Warning, Condition Monitoring

I. INTRODUCTION

Road-surface defects such as potholes, cracks, bumps and depressions affect vehicle safety, ride comfort, maintenance cost and transportation efficiency. Conventional road inspection commonly depends on periodic surveys or specialized inspection vehicles. Such approaches can provide useful information but may be expensive, time-consuming or difficult to scale across large road networks. The growth of smartphones, vehicle cameras, low-cost sensors and machine-learning methods has created opportunities for continuous and automated road-condition monitoring.

Early mobile sensing research demonstrated that accelerometers and GPS could be used to identify road anomalies and associate them with geographic positions [15], [16]. Automated sensing systems transmitted sensor observations to central servers [16], while crowdsensing approaches used observations from multiple road users to describe surface conditions [1], [2]. These studies established the feasibility of low-cost, geographically referenced road monitoring.

Computer-vision research subsequently enabled direct visual identification of potholes and other road damage. Deep learning, particularly convolutional neural networks and YOLO-family object detectors [6], has become prominent because these models can learn visual features from annotated road images. Public datasets such as RDD2022 [4] have further supported benchmarking across multiple countries and road-damage categories.



Recent research increasingly considers real-time deployment, adverse environmental conditions, edge or mobile computing, GPS/GIS mapping and hazard-aware warnings. However, these capabilities are often studied as separate components or under controlled experimental conditions. A literature survey is therefore useful for comparing the methods, identifying recurring limitations and defining an integrated direction for a practical system such as Pothoscape.

II. LITERATURE SEARCH METHODOLOGY

This survey follows a structured search-and-synthesis approach. The search strategy defines where and how literature was located, the selection criteria define which studies were retained, and a thematic comparison was then used to identify the research gap motivating Pothoscape.

A. Search Strategy

The search targeted peer-reviewed journals, conference proceedings and widely cited preprints and benchmark-dataset papers, using Google Scholar, IEEE Xplore, ScienceDirect and arXiv as the main sources. Searches covered studies published from 2014 to 2026 so that early smartphone-sensing work and recent real-time deep-learning systems could be compared within one timeline.

Keywords were organized into four concept groups and combined with Boolean operators: (i) problem terms (“pothole detection”, “road damage detection”, “road surface monitoring”); (ii) sensing terms (“smartphone accelerometer”, “GPS”, “crowdsensing”, “inertial sensor”); (iii) method terms (“computer vision”, “deep learning”, “YOLO”, “object detection”); and (iv) application terms (“real-time”, “hazard warning”, “GIS mapping”, “road condition monitoring”). A representative query was: (“pothole detection” OR “road damage detection”) AND (YOLO OR “deep learning” OR accelerometer OR crowdsensing) AND (GPS OR GIS OR “real-time warning”).

Search results were first screened by title and abstract. Full texts of promising papers were then read, and the reference lists of key papers were checked to locate related studies (backward snowballing). Search terms were refined iteratively as new terminology appeared, such as dataset names and YOLO-version identifiers.

B. Selection Criteria

A study was included when it satisfied at least one of the following inclusion criteria: (i) automatic detection of potholes or road damage; (ii) localization of road anomalies using GPS or GIS; (iii) use of low-cost or mobile sensors such as smartphones, cameras and inertial sensors; (iv) computer-vision or deep-learning detection with a stated dataset or sensing setup; (v) crowdsourced or large-scale road monitoring; or (vi) real-time warning and decision support for road users. Studies also had to be written in English and report enough method detail to allow comparison.

A study was excluded when it (i) dealt with pavement engineering, materials or structural analysis without automated detection; (ii) offered only a brief abstract, an opinion piece or no description of its method or data; (iii) was a duplicate or a minor extension of an already included work with no new contribution; or (iv) was not accessible in full text.

Among the studies satisfying these criteria, priority was given to work that was recent, methodologically clear, widely cited or practically relevant to low-cost deployment. Each selected study was recorded in a comparison matrix covering the problem addressed, sensing approach, computational method, dataset or data source, principal finding and reported limitation (Table I).

C. Synthesis

The survey emphasizes synthesis rather than paper-by-paper description. The selected literature is grouped into sensor-based monitoring, computer-vision and deep-learning detection, datasets and benchmarking, crowdsensing and mapping, and integrated real-time road-safety systems. Repeated limitations across these groups were then compared to derive the research gap addressed by Pothoscape.



III. LITERATURE REVIEW

A. Sensor-Based and Smartphone Road Monitoring

Before deep-learning vision systems became widespread, researchers investigated vehicle-motion signals as indicators of road anomalies. Smartphone-based systems demonstrated that an accelerometer can capture vertical acceleration events caused by potholes and bumps, while GPS can provide the corresponding geographic position [15]. Automated sensing architectures also showed that observations could be transmitted to a central server for analysis [16], establishing an early model for continuous road-condition monitoring.

Crowdsensing extended this concept by combining observations from road users [1], [2]. Such systems can reduce dependence on specialized survey vehicles and can cover roads through ordinary mobile devices. However, sensor signals are influenced by vehicle type, device placement, speed, suspension characteristics and driving conditions. Consequently, sensor-only methods can indicate that an anomaly occurred but may provide limited visual information about its shape, appearance or severity.

B. Computer Vision and Deep-Learning-Based Detection

Image-based road-damage detection addresses a major limitation of sensor-only approaches by directly analyzing the visual appearance of the road. Maeda et al. [3] introduced a large-scale road-damage dataset and demonstrated deep-learning-based detection using images captured through smartphones. The work also highlighted the importance of identifying damage type, because maintenance decisions require more information than a simple damaged/not-damaged classification.

Subsequent studies have investigated CNN and YOLO-family models for pothole detection [5], [6]. YOLO-based detectors are attractive for mobile and vehicle applications because object detection can be performed in a single inference pipeline. Comparative studies have reported strong performance from newer YOLO versions [13], while other work has focused on improving feature extraction, handling small potholes and reducing false detections caused by shadows, water stains and road markings [8], [10], [11].

The literature also shows that visual detection is strongly affected by the conditions represented in the training data. Low light, weather changes, shadows, road texture and regional differences can reduce generalization. Multi-weather datasets [9] and image-enhancement techniques therefore represent important directions for robust deployment.

C. Datasets, Benchmarking and Geographic Diversity

The availability of common datasets has improved comparison between road-damage detection methods. RDD2022 [4] contains road images from multiple countries and includes potholes together with several crack categories. Multi-country data can improve benchmarking, but it also highlights a deployment challenge: a model trained on one visual environment may not perform equally well on another region because road materials, markings, lighting and damage patterns differ.

For Pothoscape, this issue is particularly important because the intended deployment is localized initially to Nashik. A practical system should therefore collect and evaluate representative local road imagery instead of assuming that a model trained on a generic dataset will be equally reliable in every local condition.

D. GPS, Mapping and Crowdsensing

Location is a key component of road-condition intelligence. GPS-enabled sensing systems can associate detected anomalies with coordinates, allowing observations to be visualized geographically and used for maintenance planning. Crowdsensing further allows repeated observations of the same road segment to build a more complete picture of road quality.

Mapping alone, however, does not automatically create a driver-safety solution. A useful road-safety platform should connect the detected location with the vehicle's current position and provide a warning before the vehicle reaches the hazard. This creates a transition from passive road-condition reporting toward proactive road-user assistance.



E. Integrated Real-Time Detection and Warning

Recent systems combine mobile cameras, GPS and inertial sensors with lightweight deep-learning models to detect multiple road hazards in real time. RoadGuard [14], for example, integrates a YOLOv8n INT8 model with smartphone camera, GPS, accelerometer, gyroscope and speed information for road-hazard detection, warning and route-level decision support. Other recent studies have combined YOLO detection with GPS/GIS mapping and depth information for automated pothole mapping [12].

These integrated systems are closely related to the direction of Pothoscope. At the same time, they demonstrate that the main engineering challenge is not only detection accuracy. A deployable system must balance accuracy, latency, hardware cost, connectivity, localization quality, environmental robustness and usability.

IV. COMPARATIVE ANALYSIS OF EXISTING STUDIES

The following matrix summarizes representative studies across the main research directions. It is intended to highlight similarities, differences and limitations rather than rank the studies by a single accuracy value.

TABLE I: Comparison of Representative Road-Damage and Pothole Monitoring Studies

Study	Approach	Data / Sensors	Main Contribution	Key Limitation
Bermúdez et al. (2014) [16]	Automated mobile sensing	GPS + 3-axis accelerometer	Detects high-energy road events and transmits observations	Primarily vibration-based; limited visual detail
Singh et al. (2017) [1]	Smartphone crowdsensing	GPS + accelerometer	Road-condition monitoring through crowdsourced observations	Sensor readings vary with vehicle/device conditions
Li & Goldberg (2018) [2]	Mobile crowdsensing	GPS + accelerometer	Identifies and locates bumps/potholes using citizen sensing	Position and signal quality depend on mobile sensing conditions
Maeda et al. (2018) [3]	Deep-learning road damage detection	Smartphone road images	Large-scale road-damage dataset and visual detection	Visual performance depends on dataset diversity
Arya et al. (2022) [4]	RDD2022 dataset	47,420 images from six countries	Provides multi-country benchmark data for road damage	Dataset coverage does not guarantee local deployment robustness
Automatic Pothole Detection (2023) [5]	Object detection	Road-damage images	Compared Faster R-CNN, Sparse R-CNN and YOLO variants	Accuracy remains dependent on country-specific data
Road Safety / YOLOv5 (2024) [7]	YOLO-based in-vehicle detection	Vehicle camera / image-video data	Detection plus pothole dimension/location estimation	Requires suitable training and vehicle data
Robust Multi-Weather YOLOv9 (2025) [9]	Enhanced YOLOv9	Multi-weather pothole dataset	Improves robustness under varied weather conditions	Model complexity and dataset requirements
Road Surface Damage / YOLOv8 (2025) [10]	Enhanced YOLOv8	Multiple road-damage datasets	Improves feature extraction for road defects	Primarily detection-focused



Study	Approach	Data / Sensors	Main Contribution	Key Limitation
Real-Time YOLO Models (2026) [12]	YOLO10/11 + GPS/GIS	13,767 images + GPS; depth camera	Fast pothole detection with mapping and deployment interface	Requires integrated compute, positioning and data pipeline
RoadGuard (2026) [14]	Mobile hazard intelligence	Camera + GPS + IMU + speed	Detection, warning and hazard-aware routing	Broader system complexity and deployment requirements

V. RESEARCH GAP

The reviewed literature demonstrates substantial progress in automated road-damage detection, but several recurring gaps remain. First, sensor-based systems can locate road anomalies at low cost but may lack visual characterization. Second, vision-based systems can identify potholes more directly but depend on camera quality, training data and environmental conditions. Third, GPS/GIS systems can map hazards but mapping by itself does not guarantee timely driver warning. Finally, integrated real-time systems combine several technologies but may increase hardware, computation, connectivity and implementation complexity.

Another important gap is the difference between laboratory or dataset-level performance and continuous local deployment. A model can achieve strong benchmark results while still facing difficulties caused by local road appearance, shadows, rain, night-time conditions, camera placement, vehicle vibration and network availability. Repeated observations and local data can therefore be valuable for improving reliability over time.

Based on these observations, the literature supports the need for a practical integrated workflow that combines automatic pothole detection, geographic localization, proactive warning and centralized road-condition intelligence while keeping the hardware and operating cost appropriate for local deployment. Pothoscape is positioned around this integration rather than claiming that pothole detection itself is a new research problem.

VI. POTHOSCAPE: PROPOSED INTEGRATED APPROACH

Pothoscape is proposed as a road-intelligence and safety platform in which a vehicle-mounted sensing unit observes the road ahead, detects potholes automatically and associates detected hazards with their geographic location. The detection event can be transmitted to a cloud database, where repeated observations can contribute to a continuously updated road-condition map.

The intended workflow is:

ROAD AHEAD → CAMERA AND SUPPORTING SENSORS → POTHOLE DETECTION → GPS LOCATION → DRIVER ALERT → CLOUD DATABASE → POTHOSCAPE APP → AUTHORITY DASHBOARD.

The system is designed so that automatic detection is the primary interaction rather than requiring the driver to manually report every pothole.

For road users, the important output is an early warning when a detected hazard lies ahead. The warning can be delivered through a vehicle display, phone notification and/or audio alert depending on the deployment platform. The warning distance should be determined experimentally using vehicle speed, localization accuracy, detection latency and safe stopping or avoidance requirements rather than using a fixed distance without validation.

For authorities, aggregated observations can provide a map of recurring pothole locations and road-condition hotspots. Repeated detections from different trips can potentially increase confidence in a hazard and support maintenance prioritization. This transforms individual detections into a shared road-intelligence layer.

VII. CHALLENGES AND LIMITATIONS

The literature identifies several practical challenges relevant to Pothoscape. Detection accuracy may decrease in low-light, rainy or visually complex conditions. Small or partially occluded potholes can be difficult to detect. Camera



position and vehicle motion affect image quality, while sensor placement influences accelerometer readings. GPS errors can shift the reported location, especially in dense urban environments.

Connectivity is another consideration. A road-safety warning should not depend entirely on continuous cloud connectivity if a local or previously downloaded hazard record can provide useful information. Cloud synchronization can be used for updating the shared database when connectivity is available.

Finally, the system should be evaluated using real road conditions and multiple vehicle types. A model that works in a car may need different sensor mounting or warning mechanisms for a two-wheeler. These constraints should be included in future experimental validation.

VIII. FUTURE SCOPE

Future work can focus on building a local Nashik road-damage dataset and evaluating lightweight YOLO-family models under daylight, low-light and weather variations. Sensor fusion can be investigated to combine visual evidence with vehicle-motion signals and improve confidence in difficult cases.

The cloud layer can be extended to maintain hazard history, confidence scores, repeated detections, severity categories and road-segment statistics. A future authority dashboard could support filtering by location, frequency and severity to help prioritize maintenance.

Additional work can investigate offline-first operation, edge inference, efficient model compression, two-wheeler warning interfaces, route-level hazard prediction and automatic identification of other road hazards such as cracks, speed breakers and damaged surfaces.

IX. CONCLUSION

This literature survey reviewed the development of automated road-condition monitoring from smartphone sensor systems and crowdsensing to computer-vision, deep-learning and integrated real-time hazard systems. The reviewed research confirms that pothole detection can be approached using both physical road-response signals and visual information, while GPS and cloud systems enable geographic organization of observations.

The comparison also shows that no single technique eliminates all deployment challenges. Sensor-based systems are relatively accessible but may provide limited visual characterization; vision-based systems offer direct identification but depend on data and environmental conditions; and integrated systems provide richer functionality at the cost of greater engineering complexity. These observations motivate Pothoscape's integrated direction: automatic detection, location tagging, proactive warning and continuously updated road intelligence within a practical low-cost deployment framework.

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