SCIENTIFIC PAPER
Published: April 18, 2026
https://doi.org/10.13167/2026.32.7

AI for pavement distress detection on lower-ranking roads: A bibliometric and systematic review

Martina Zagvozda[1], Kristijan Ljutić[2]✉, Vjekoslav Janić[3] and Ivana Barišić[1]

[1] Josip Juraj Strossmayer University of Osijek, Faculty of Civil Engineering and Architecture Osijek, Vladimira Preloga, 3, 31000, Osijek, Croatia

[2] 4D - monitoring d.o.o., Kukuljanovo, 182/2, 51227, Kukuljanovo, Croatia

[3] Public fire department Vukovar, Trg Matije Gupca 2, 32000, Vukovar, Croatia

Corresponding author:
Kristijan Ljutić

Received:
November 28, 2025

Revised:
March 6, 2026

Accepted:
March 23, 2026

Published:
April 18, 2026

Citation:
Zagvozda, M. et al.
AI for pavement distress detection on lower-ranking roads: A bibliometric and systematic review.
Advances in Civil and Architectural Engineering, 2026, 17 (32), pp. 116-136.
https://doi.org/10.13167/2026.32.7

ADVANCES IN CIVIL AND ARCHITECTURAL ENGINEERING (ISSN 2975-3848)

Faculty of Civil Engineering and Architecture Osijek
Josip Juraj Strossmayer University of Osijek
Vladimira Preloga 3
31000 Osijek
CROATIA

Abstract:
Artificial intelligence (AI) and deep learning have transformed pavement condition assessment by enabling faster, more consistent, and scalable detection of pavement distresses compared with traditional manual inspection. Although significant progress has been made in detecting cracks and other common defects, limited attention has been given to developing AI-based approaches tailored to the specific needs of lower-ranking roads, where potholes, ruts, manholes, and localised surface irregularities occur more frequently and present substantial safety concerns. This paper presents a combined bibliometric and systematic review of recent advances in AI-driven pavement distress detection, with emphasis on methods applicable to low-volume road networks. A structured search of Scopus and ScienceDirect resulted in 98 relevant peer-reviewed studies. The bibliometric analysis revealed a strong increase in research activity since 2018, with China, India, and the United States of America leading the number of published articles. You Only Look Once (YOLO)-based object detection algorithms dominate current approaches, supported by variants of convolutional neural networks and emerging multi-modal techniques that incorporate unmanned aerial vehicle imagery, three-dimensional (3D) scanning, or sensor fusion. Despite rapid development in AI-driven pavement distress detection, key challenges persist, including inconsistent ground-truthing, limited comparison between AI and human evaluators, lack of standardised benchmarking datasets, and the need for robust 3D data acquisition strategies for complex distresses on lower-ranking roads. Addressing these gaps is essential to ensure reproducibility, comparability, and practical implementation of AI-based pavement inspection systems.

Keywords:
YOLO; review; pavement; pothole; lower-ranking roads

1 Introduction

Pavement condition assessment is critical to ensure roadway safety, durability, and cost-effective maintenance. Traditionally, inspection relies on manual surveys and simple mechanical devices such as straightedges and profilometers. Although these devices are reliable, they are labour-intensive, subjective, and limited in spatial coverage. Although the development of digital imaging and sensor technologies in the late 20th century introduced automated visual inspection systems, these early systems often struggled with variations in lighting, pavement texture, and data interpretation.

The emergence of artificial intelligence (AI), particularly computer vision and deep learning techniques, has transformed this sector by enabling accurate, consistent, and large-scale analysis of pavement conditions. Automated data collection and AI data processing are the two main elements of automated pavement surveys. AI algorithms can detect and classify distresses (e.g., cracks, rutting, and potholes) with far greater precision and speed than traditional methods, and these algorithms can also measure deformations in three dimensions. The adoption of AI-driven inspection systems reduces human error, accelerates decision-making, and supports predictive maintenance strategies that extend pavement life and optimise resource allocation.

In the latter part of the 20th century, researchers began experimenting with early machine learning techniques to assist image-based pavement condition assessment. For example, in 1994, traditional and neural network classifiers were compared to detect cracks in video images of asphalt–concrete pavement surfaces, showing that neural networks could improve detection and consistency under certain conditions [1].

In the 2000s, as digital imaging improved and computational power increased, researchers combined high-resolution cameras with classical image processing and shallow neural networks. For instance, a paper published in 2015 demonstrated methods for distinguishing cracks from noise in high-resolution images, aiming for practical deployment in crack-sealing machinery [2].

In 2015-2018, with the rise of deep learning (particularly, convolutional neural networks (CNNs), fully convolutional networks, and encoder–decoder architectures), there has been a surge of more accurate and automated methods.

Owing to its remarkable advancements, deep learning has emerged as the primary method for pavement defect inspection in early 2020. A universally acknowledged large-scale benchmark dataset was lacking to advance and accurately compare deep-learning methods for visual defect inspections. In addition, accessible datasets varied in terms of the type of defect, infrastructure, substance, and visual context [3].

Pavement cracks are a common issue in pavement service life and are primarily caused by traffic loads, material fatigue, climate change, and unstable foundations. Both the structural integrity and traffic safety may be affected by cracks because they may weaken the structure and cause collapse and pavement damage. Consequently, timely crack detection is essential for proper pavement maintenance and service life extension. Since the invention of data collection vehicles in the 1990s, a substantial number of image-processing-based algorithms for automatic detection and identification of pavement cracks have been proposed, and they have received the most attention from researchers [4]. Several recent reviews on automated pavement data collection and AI image processing algorithms have been published [4-8], concluding that most AI data processing methods focus only on distress classification, detection, and segmentation, and they lack in quantitative analysis of pavement distresses, such as size, area, and overall pavement condition evaluation. Furthermore, there is an absence of standardised benchmarks and evaluation systems, which are crucial for encouraging innovation and ensuring objectivity and reproducibility in model evaluation.

Cracks are common in roads at all levels of service. In the literature dealing with machine learning techniques for pavement condition evaluation, 44 % of the references deal with cracks whereas 19 % pertain to pothole analyses [9]. However, some distresses and objects such as potholes, ruts, manholes, and drains are more common in secondary roads. Potholes are the

most common type of non-cracked pavement distress and have a significant impact on travel quality and safety. Manholes and drains are common objects in urban road networks. Higher-ranking roads are subject to stricter maintenance requirements and the occurrence of major damage such as potholes and ruts is prevented by intensive inspections and systematic maintenance activities. In addition, structures such as manholes and drains are not allowed on the pavement of higher-ranking roads owing to high-speed and heavy-goods vehicle traffic, which would endanger traffic safety and pavement service life. On lower-ranking roads, there is a more intense localised load because the pavement is narrower than on higher-ranking roads, and the utility infrastructure is often routed under and along the edge of the pavement. Therefore, on lower-ranking roads, cracks, potholes and ruts should also be analysed because these damages occur more quickly, directly endangering traffic safety and comfort, and are related to the presence of utility infrastructure.
This review paper synthesises recent research on AI applications in pavement visual inspection and deformation measurement with an emphasis on methodological advances, performance outcomes, and broader implications for future infrastructure management. This paper focuses on the current state-of-the-art in automated pavement data collection and AI image processing algorithms that are particularly applicable and relevant to lower-ranking road maintenance activities.

2 Methodology

2.1 Bibliometric analysis and literature review

Bibliometric analysis has become an increasingly popular technique in academic research in recent years because of the vast number of articles published annually and the exponential increase in scientific knowledge [10; 11]. It is a thorough technique used to examine and assess scientific data, identify papers on relevant topics, and conduct a systematic study of literature. Bibliometric analysis allows the identification of patterns and trends within a vast number of studies on a given subject, the occurrence of keywords, and the number of citations, thus providing a basis for a comprehensive literature review. The steps involved in bibliometric analysis are shown in Figure 1, starting by clearly defining the research objectives and questions. Subsequently, data collection is conducted by selecting established literature databases such as Scopus and Web of Science, identifying search terms, and performing a literature search. More than likely, such a search will result in hundreds, if not thousands, of sources that should be screened and filtered, and duplicates removed. The dataset is then analysed, and the results are visually presented prior to interpretation of the findings and report creation.

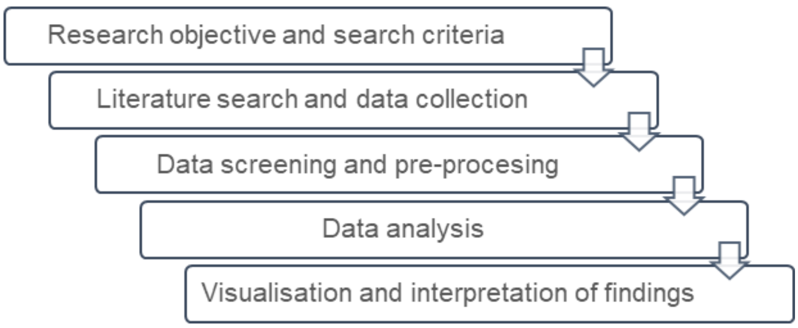


Figure 1. Bibliometric analysis process

2.2 Research questions

When managing secondary road networks, local and municipal authorities must consider all the specificities of such roads, including different types of pavement distresses compared with those found on highways and primary roads. Considering the growing research on the application of AI in all aspects of road management systems, one of the objectives of this study is to determine how these types of roads are included in a vast body of research. This includes determining whether the same AI models are used and trained on the basic datasets, or if the pavement distresses specific for secondary roads are included in the model training. The second objective is to determine how these AI models compare to the manual inspection by trained humans, either on datasets or under real field conditions. Furthermore, the ability to measure not only the two-dimensional (2D) surface but also the depth of distress helps to better classify the severity of distresses. The objective of this review is to determine the possibilities and technologies for gathering three-dimensional (3D) distress information. Finally, since You Only Look Once (YOLO) is shown to be a prevalent AI architecture used in distress determination, this review aims to determine the most used and best-suited YOLO versions, their benefits and drawbacks, and compare them with other AI architectures.

2.3 Selection of databases and keywords and search queries

The Scopus database was selected in this study, and a query was conducted using the keywords listed in Figure 2. Scopus is a literature database that allows the use of Boolean syntax in queries to obtain more precise results. Examples of the Boolean syntax are the “OR” operator that broadens the search that includes all articles with given terms, as well as the “AND” operator that results in articles that fulfil all criteria. Using this method, 211 articles were first identified, after which the inclusion and exclusion criteria were set to narrow down the list of articles. First, the list was limited to articles published in English. Next, the query was limited to journal or conference articles to obtain a certain quality assurance, as they were peer-reviewed. Following this, the research field was limited to engineering, computer science, multi-disciplinary science, and related sciences, whereas medicine, biology, chemistry, business, and economics were eliminated, significantly reducing the number of articles. However, even with careful keyword selection and set limits, several articles were obtained that addressed vastly different topics that were not in the field of pavement management. For instance, manhole or culvert inspection with AI algorithms rather than its detection on pavements. Thus, further screening was performed by reading all abstracts and excluding a number of articles that did not use convolutional neural networks (CNNs) or YOLO algorithms for pavement distress detection, such as potholes, manholes, and culverts.

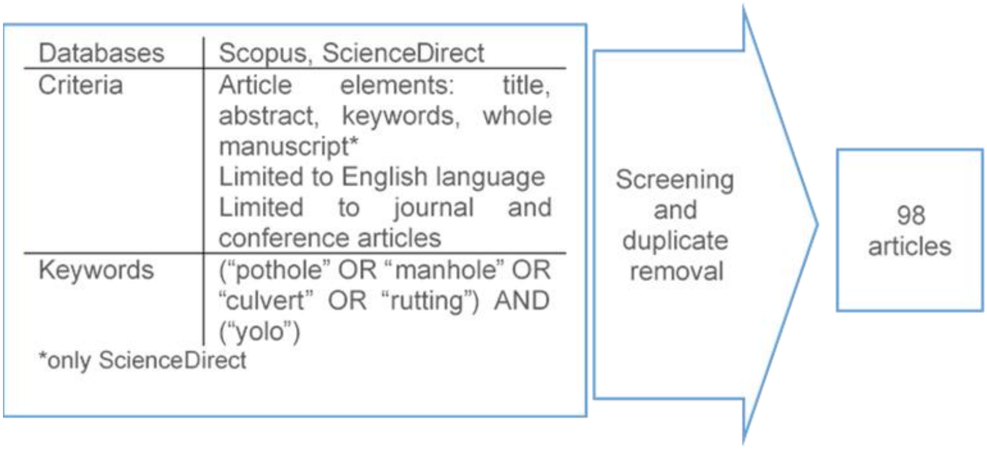


Figure 2. Literature selection process

However, because Scopus is a citation database, it does not contain the full text, and thus, every search was conducted by analysing the titles, abstracts, and keywords. By examining the full articles and applying the snowballing method, there were a large number of articles on research subjects that did not have some search terms included in either the title, keywords, or abstract, but they were in the full text. For instance, YOLO algorithms were used as the main tool in the study but they were not mentioned in the abstract and they only referred to using more general or umbrella terms, such as artificial intelligence or CNN. Therefore, ScienceDirect (a database from the same publisher as Scopus) was also searched using the same query and the full articles were analysed to include additional literature. Bibliometric data were downloaded from either the Web of Science (WOS) or Scopus database using their digital object identifiers (DOIs). The article lists and their bibliometric data were then combined into one database and duplicates were removed.

2.4 Tools used in the bibliometric analysis and systematic literature review

The full combined list of articles consisted of 117 articles that were read, analysed, and classified based on quality criteria, after which both bibliometric analysis and systematic literature review were conducted. For bibliometric analysis, Bibliometrix software was used along with Litmaps to determine the research connections.

Bibliometrix is an open-source tool created in the R language environment that provides a set of tools for quantitative bibliometric research [12]. This tool allows scientific mapping analysis of scientific literature, statistical analysis of bibliometric data, coupling, co-citations, and co-words, as well as collaboration analysis. In addition, this tool provides graphical illustrations and representations of the analysed data. In addition, the Litmaps tool was used to map research connections over time, track topic development and co-citations of the acquired publication databases, and visualise them.

The articles were systematically reviewed by reading through all of the articles, critically systematising, and discussing the available findings.

3 Bibliometric analysis results

Query, screening, and duplicate removal resulted in 98 articles published from 2020 to 2025. Interest in the application of AI for pavement distress detection has grown significantly over the past six years, as evident from Figure 3, which shows the number of articles published annually on this topic. It can be observed that there is a constant growth in the number of articles published within this period, indicating an increasing interest in the research and application of different AI models for pavement management, namely, pavement distress detection and classification. The largest number of articles was published in 2025, almost doubling each of the previous years, with a total of 38 articles, constituting approximately 40 % of the reviewed articles.

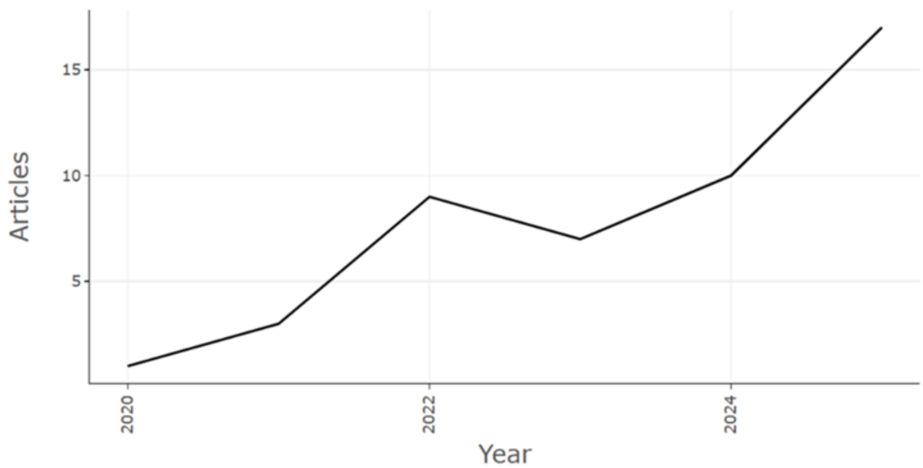


Figure 3. Number of articles pertaining to the use of AI algorithms in pavement distress detection published from 2020 to 2025

The largest number of articles originated from China (36 %), followed by India (17 %), and the United States of America (8 %), with other 24 countries contributing a lower number of articles.

The spatial distribution of the frequency with which authors from a given country contributed to the number of reviewed articles is shown in Figure 4.

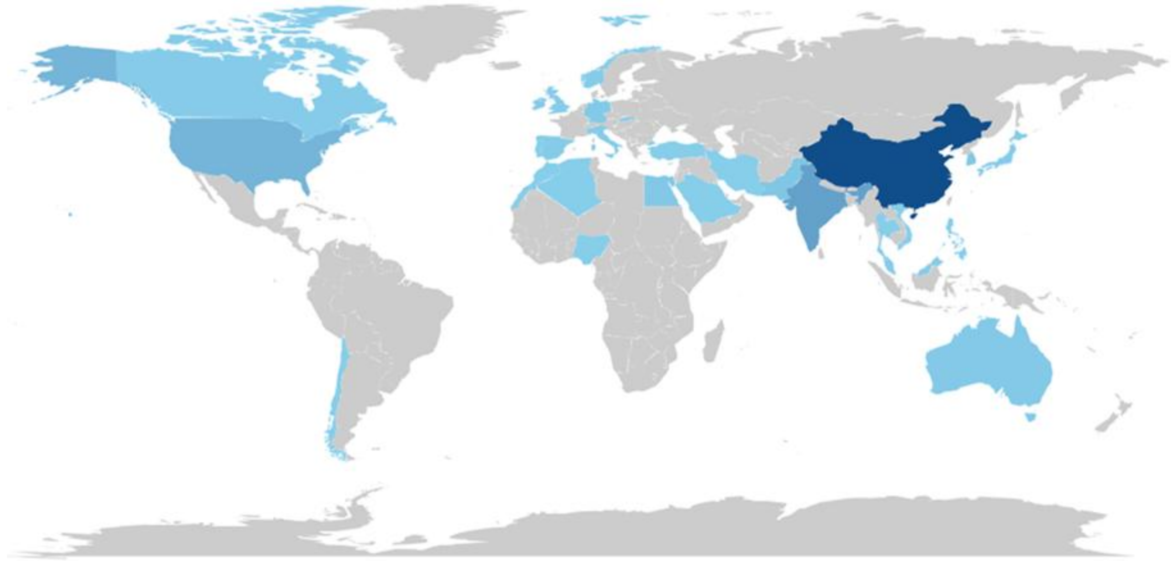
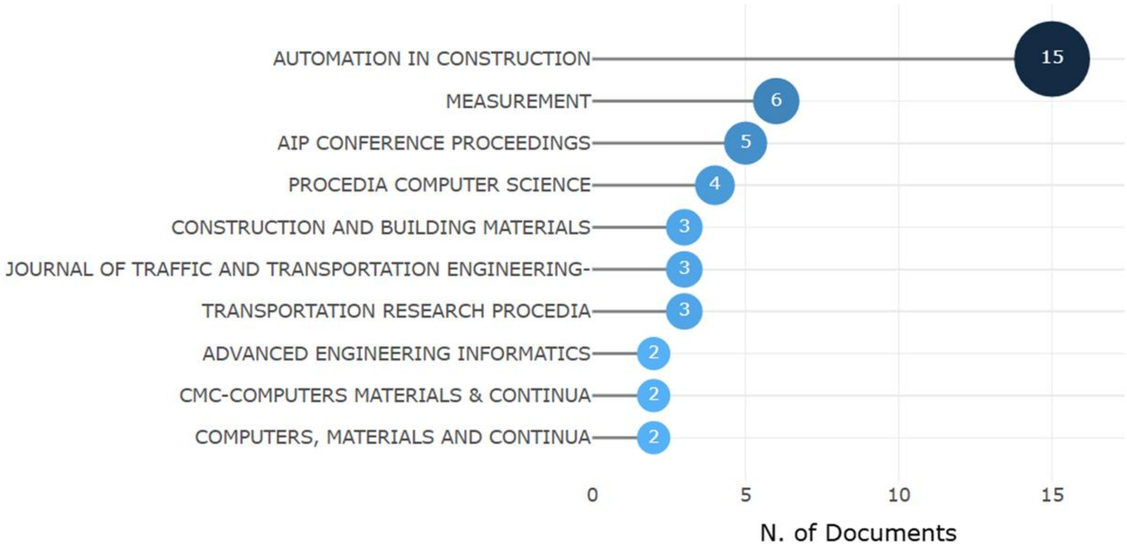
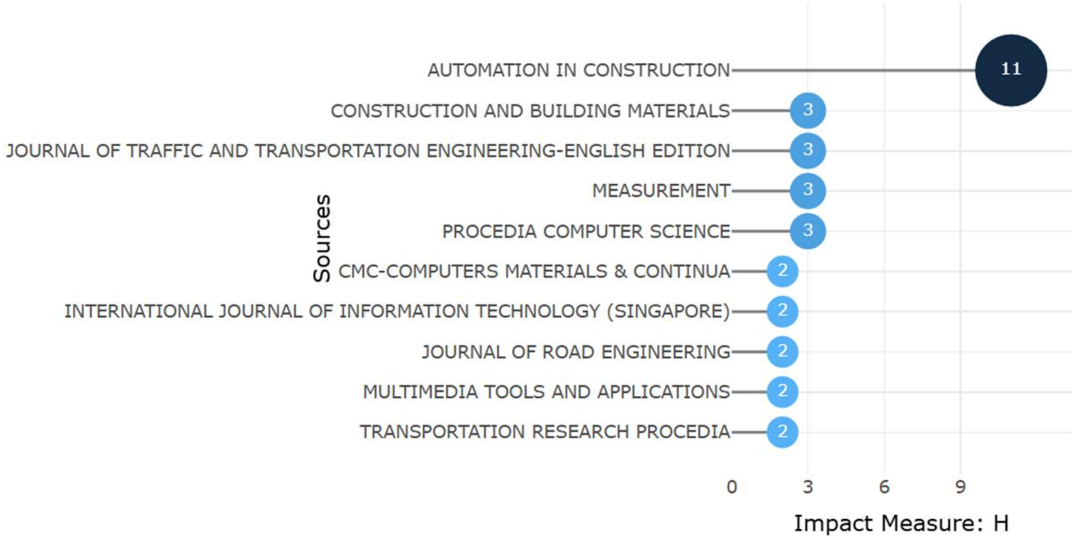


Figure 4. Spatial distribution of the frequency with which authors from a specific country contributed to the number of reviewed articles

As mentioned earlier, the search query was limited to journals (93 %) and conference articles (7 %), with Automation in Construction being the most relevant, with the highest number of published articles and highest local impact measured by the H-index among the gathered datasets (Figure 5). In terms of the general impact and citations, two articles stand out (Zhu et al. [13] and Majidifard [14]), with 187 and 177 global citations, respectively. The number of global citations for articles published in 2022 and 2020 further demonstrates how current and developing this field is. The results obtained from bibliometric analysis were further validated by an analysis of Litmaps (Figure 6). Here, along with the article distribution over time and citation data, the co-citations and linkages between articles are displayed. This further demonstrates the significance of these initial articles, and how often they are referred to and cited in later studies.



a)



b)

Figure 5. a) Most relevant sources; and b) their local impact based on the H-index

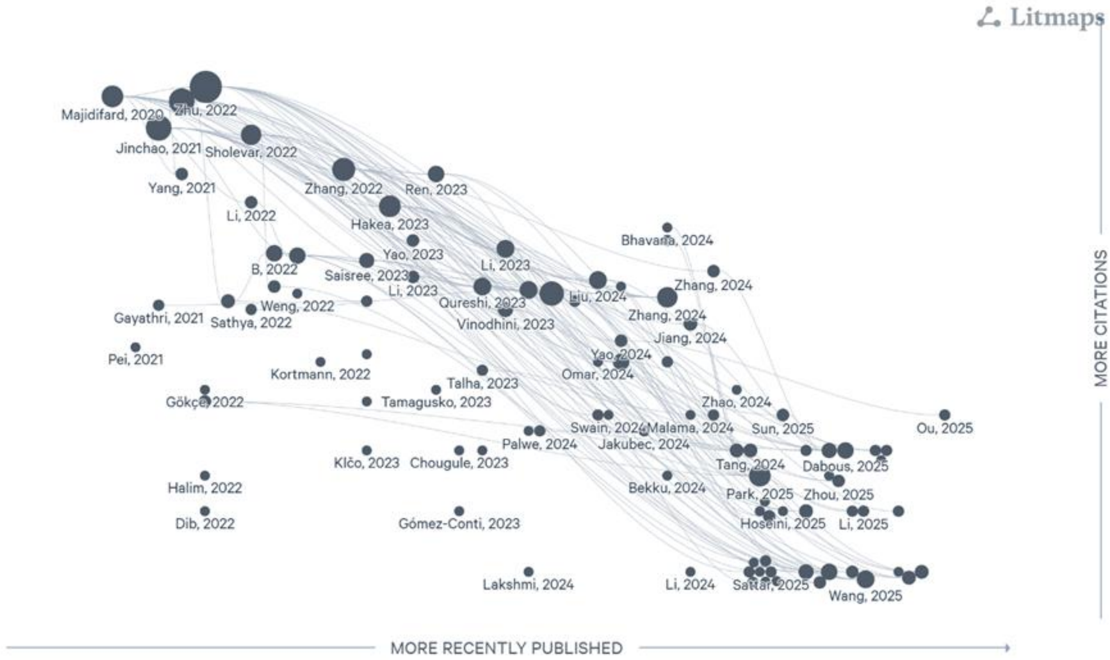


Figure 6. Co-citations and linkages between the articles

Analysis of the trending topics (Figure 7) or how the occurrence of each topic changes throughout the years shows that from 2020 to 2025, the initial studies begin with broader or generic terms, such as machine learning, image processing, and road maintenance. This is the first exploratory use of AI in pavement management. With the progression of time and the development of AI algorithms, their application has become narrower and more focused. Therefore, machine learning is replaced with terms such as CNN or even YOLO later on, which further distinguishes which form of AI architecture or AI algorithm is used. Recently, terms such as attention mechanisms or other modifications of known algorithms have been increasingly mentioned as they are used to improve existing models. For pavement management, which is a broad term, the focus shifts to road damage, damage detection, and object detection of potholes, further demonstrating the development of the field and how current this research is.

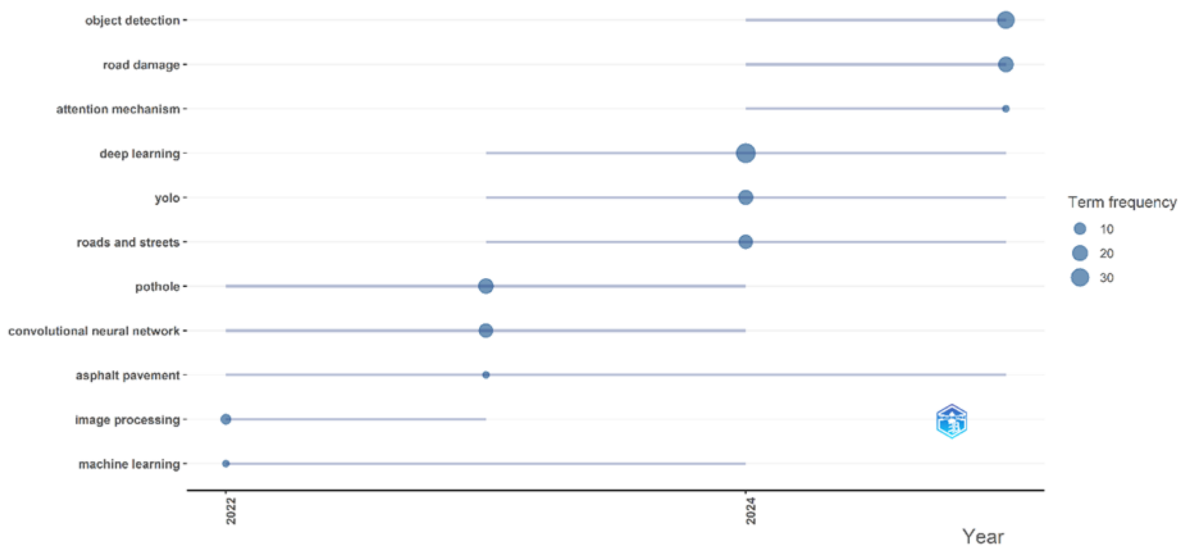


Figure 7. Analysis of trending topics

4 AI framework

To understand the role of image processing, YOLO algorithms, and other AI models used in pavement distress detection and classification, a framework explaining their relations and functions should be set.

Object detection, a part of computer vision, highly benefits from the development of AI as it provides solutions that are capable of working with big data within a short period and with high accuracy. Through image processing, objects can be detected, their precise locations in the image can be determined, and the objects themselves can be classified [15]. Object detection can be performed using different algorithms [16], with deep-learning neural-network-based algorithms having wide applications because of their accuracy and robustness.

To put it in context, AI has multiple sub-fields, one of which is machine learning (Figure 8). Machine learning is designed to emulate human intelligence by training the model on large datasets to learn patterns and make predictions [17]. Machine learning has its own sub-sets, classified into supervised learning (task-driven), unsupervised learning (data-driven), and reinforcement learning (where it learns from its own mistakes) [17]. Deep learning is a supervised learning technique suitable for image and speech recognition and it is based on the training of neural networks with multiple layers. CNNs are a type of neural networks used for various tasks; however, they are particularly successful in image recognition [18], and thus, they are often applied for pavement condition assessment. They consist of a series of convolutional layers used for the analysis of input images, after which the fully connected layers make predictions. Once trained on large sets of labelled data, they can make predictions on unlabelled images and label them with the highest probability.

YOLO is a real-time object detection algorithm based on CNN. YOLO was proposed by Redmon et al. [19] in 2015, with up to 11 subsequent versions developed over the years [15; 20]. YOLO is a one-stage detector, which means that operations are performed using a single CNN. YOLO is trained on large datasets and treats object detection and classification as an integrated regression problem, thereby determining the position and category of a bounding box in a single pass through a neural network. Through architectural changes and various optimisations in each subsequent version, YOLO's detection accuracy and speed have improved, making it preferred for a wide range of applications. Different industrial sectors, agriculture, security systems, and even medicine, where the detection of small objects is crucial, benefit from YOLO's real-time image processing [16]. In traffic and transportation engineering, YOLO is commonly preferred for vehicle and pedestrian detection, and in

autonomous vehicles, YOLO is used for parking systems as well as different aspects of pavement management systems (PMSs).
Along with YOLO, other deep learning methods such as recurring CNN (R-CNN), Fast R-CNN, Faster R-CNN, and Mask R-CNN have been used in pavement condition assessment based on the reviewed articles. These methods use two-stage detection to improve accuracy, but this comes at the expense of extended processing time. Object detection models that are usually used are YOLO-based models (44 %) and R-CNN-based models (30 %) [9].
In addition to damage detection from images of existing roads and distresses, AI can also be used to create synthetic images for training detection models. An example is General Adversarial Network (GAN), which is also a form of deep learning, and it is used in [21] to augment available data with synthetic images and then train detection models for pothole detection in adverse weather.

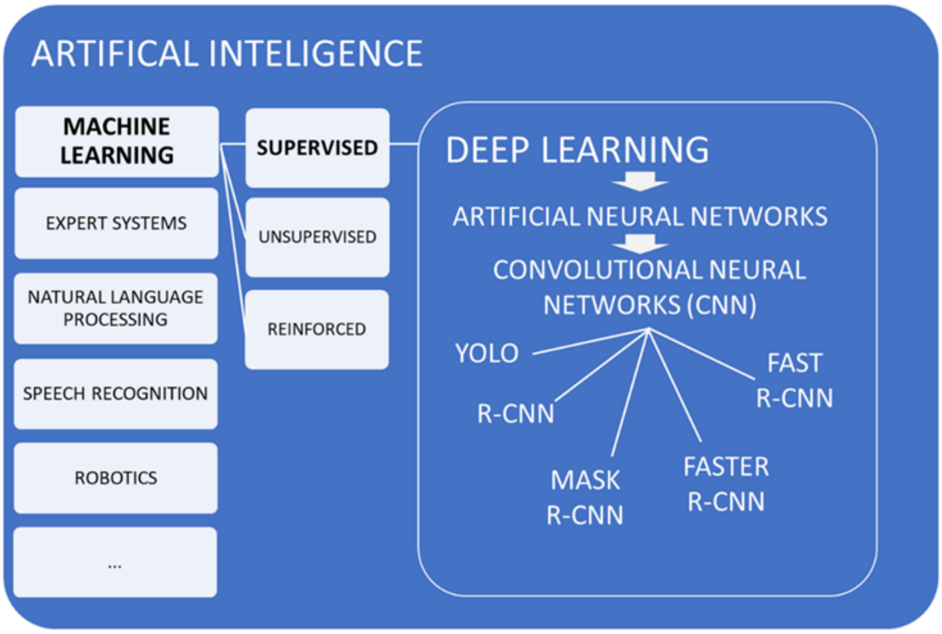


Figure 8. AI framework

5 Discussion

5.1 Ground truth for AI model evaluation

Traditionally, pavement condition assessment relies on manual inspection, which is labour-intensive, inconsistent, and costly. Modern technologies in form of computer vision, image processing, and machine learning represent the basis for the implementation of automated pavement condition assessment. A significant number of studies deal with different algorithms for pavement distress assessment, highlighting their efficiency and precision. However, for efficient and accurate identification, new methodologies must be compared with traditional methods. Based on the systematic literature review, it is found that there are limited studies that compare human, manual inspection, and AI-generated results (Table 1). Digital datasets used for pavement distress identification and annotation by humans (usually trained experts or students) are also typically used for AI-based model analyses. The results mainly identify AI-based models that closely match human performance or even outperform human evaluators. However, there are limited studies comparing real field conditions, manual inspection, visual inspection, and AI-based models. Comparative studies of pavement distress identification from the same dataset conducted by a significant and statistically relevant number of human evaluators and AI models are also lacking. Most of the time, the exact number of trained experts participating in the study is limited to 5 or it is not specified. Although some studies involved human raters who manually labelled the distresses (annotated collected images of pavement distresses) [22; 23], none of these studies compared the results obtained from the AI-based models and raters' assessments. In [24], human raters (two experts) were responsible for annotating images using Pavement Surface Condition Index (PSCI) ratings, which served as the ground truth for training the deep learning models.

Table 1. Review on AI versus human evaluator studies

Algorithm	Research specifics	Ground truth*	AI / human	Reference
CNN, YOLOv4-tiny Deep SORT	Different light, speed, and road condition environments	Actual number of potholes	> 80% / ≤ 80%	[25]
Modified generative adversarial network (GAN)	New real-time method, comparison of annotation results done by experts and students	Human detection on a newly recorded dataset	84% / 86%	[26]
Modified faster R-CNN	Patching and non-slip area detection	Human detection on a newly recorded dataset	77% / ---	[27]

**Absolute reference value*

5.2 Purpose of AI models in pavement distress detection

In general, the development of AI models for pavement distress detection has two purposes: (1) to support the development of autonomous vehicles, and (2) to enhance pavement maintenance activities. The same or similar AI models can be used for both purposes, but how they are trained and configured may vary, given that their goals are to avoid hazards or quantify pavement conditions.

AI-based models developed for autonomous vehicles and infrastructure development seek to minimise accident risks and improve overall travel safety by enabling vehicles to detect and avoid potential hazards. These models have been used to enhance the vehicles environmental awareness and localisation capabilities in a dynamic context [28-40]. Most of the reviewed studies are oriented towards timely detection and identification of potholes; however, some studies have identified other pavement objects such as speed breakers [41], speed bumps, and manhole covers [42] which are characteristic objects of low-volume roads.

Other studies have contributed to road and pavement maintenance by improving pothole detection methods. The primary purpose of these methods is to enhance pavement damage identification for better road maintenance decision-making, thereby accelerating the deployment of non-destructive automated road damage detection systems. Such systems are crucial for maintaining roadway infrastructure, supporting economic activity, and ensuring public safety by maintaining roads in good condition. A number of studies has addressed a range of roadway hazards, such as cracks, oil stains, patches, and pebbles [43], dropped objects [44], and accurate pothole localisation to prioritise repairs [45]. Additional studies have focused on improving traffic flow and reducing congestion through adaptive control strategies, particularly during sudden traffic surges or accidents [46], and detecting pavement damage in urban environments [47]. Further research has been carried out to identify potholes and speed bumps [48], detect potholes and speed breakers [49], evaluate rural road pavement conditions [24], and identify potholes on muddy and highway roads [50]. Other developments include platforms intended to support the digitalisation of forest roads for more efficient operation and management [51], systems targeting the detection of cracks, potholes, and rutting [52], methods capable of distinguishing overlapping target pixels, differentiating fine-scale distresses from large-scale block patches [53], and detection of non-slip areas and pavement conditions in urban environments [27]. Overall, the number of published studies demonstrates the growing importance and relevance of automated pavement damage detection for effective roadway maintenance and management, particularly potholes and other defects on lower-ranking roads [9; 13; 21-23; 26; 28; 54-83]. Finally, there are some studies that deal with real-time pavement condition assessment for both purposes, not only enhancing pavement maintenance activities for advanced autonomous vehicle development [84-92] but also alerting visually impaired individuals to enhance their safety while navigating roads [93].

5.3 Data collection

Knowing how images are collected is crucial for automated pavement condition assessment, because the quality, consistency, and context of the data directly determine how well AI-based models perform. Several complex hardware components, each intended for a particular purpose, make up the pavement data collection system. Right-of-way (ROW) cameras, ground penetrating radar (GPR) devices, light detection and ranging (LiDAR) devices, sophisticated laser imaging systems, and other tools can be used in automated pavement condition surveys [72].

ROW cameras are primarily used to collect pavement distress images [22; 26; 29; 32; 36; 41; 42; 52; 73; 80; 84; 94; 95]. Cameras may be used alone, and smartphone cameras are especially practical. These cameras may be integrated with other hardware systems as part of an automated data collection vehicle. Some researchers have used thermal camera [54] and infrared camera [71] for pothole identification. Unmanned aerial vehicles (UAVs) have also been used [56; 75; 97], typically at a flight altitude of 20-30 m as a fast method for data collection.

In addition to creating their own databases by collecting roadway camera footage, a significant number of studies make use of existing publicly available databases. According to a review presented in [9], 78 % of datasets used in machine-learning-based distress detection models are private, whereas the remaining 22 % are public datasets. These databases are used alone or in combination with databases created using previously mentioned techniques [31; 32; 81; 86; 91]. Online databases from traffic surveillance datasets [28], Google, and Kaggle (Road Damage Dataset (RDD)) [21; 30; 33; 37; 50; 55; 58; 59; 85] or the Roboflow public library [57; 78; 93] are typically used. One of the most widely used open-source pavement distress detection datasets is the RDD, and the latest version (RDD2022) contains more than 47000 images from six countries and includes four common types of damage: longitudinal linear cracks, transversal cracks, alligator cracks, and potholes [88].

Two-dimensional data acquisition is possible using only ROW cameras, whereas 3D data are more suitable for assessment of pavement conditions of lower-ranking roads. Potholes, manholes, ruts, and road surface roughness are characteristic distresses of low-volume roads, which require a 3D approach. Three-dimensional data offer objective, quantifiable parameters, which enhance reliability and repeatability and boost the accuracy of distress classification. Three-dimensional imaging is less easily influenced by environmental conditions, including road noise caused by poor illumination conditions. Even though 3D imaging more accurately reflects the road texture, it frequently encounters issues in areas with minimal variations in height, such as during the early stages of crack development (microcracks) [98].

There are two approaches for 3D data collection. The first approach involves capturing 3D images and creating a 3D dataset, and the second approach involves capturing 2D images of pavement distresses and reconstructing 3D data. Several techniques have been used for 3D dataset creation, including camera and LiDAR [32; 84], 3D cameras and linear lasers [99], depth cameras [83], and 3D laser scanner comprising a laser emitter and camera [100]. In general, 3D data are acquired by stereo-vision-based methods or laser-based scanning methods, which are complex and expensive. In addition, these methods are sensitive and their accuracy can be affected by environmental conditions such as rain, lighting, or vibrations [54; 57].

A less expensive method is the reconstruction of 2D images into a 3D dataset, for which several approaches can be used. One approach is binocular stereo vision using two cameras to acquire images of the target in order to adjust these images to the same plane and then the 3D information is reconstructed [101]. Another approach involves using two cameras and Structure from Motion (SfM) software for 3D point cloud creation [102].

Three-dimensional pavement surface data can be used for other pavement distress detection methods, such as rutting or unevenness. The most commonly used methods for 3D imaging pavement distress detection are laser-based and stereo-imaging systems. Three-dimensional laser scanning can be performed using different set-ups based on the deployment platforms: Terrestrial Laser Scanning (TLS), Mobile Laser Scanning (MLS), and Airborne Laser Scanning (ALS). In [103], a method for extracting rutting features from ALS 3D point clouds is presented using a UAV-mounted LiDAR system. To calculate the pavement, mean profile depth (MPD), a 3D laser scanner on a movable experimental platform was constructed in [100]. However, the test was performed at a very low data collection speed, where it took 10 min per pavement area with sample dimensions of 100 × 100 mm for 3D data acquisition. A deep-learning-based multi-view stereo reconstruction method was applied for the analysis of pavement texture depth in [104], processing two datasets obtained by RGB and RGB depth cameras. The same approach of collecting depth data and RGB images from the RGB-D sensor was used in [105] to estimate the pavement roughness and International Roughness Index (IRI).

GPRs allow the assessment of pavement structural conditions and detection of damage below pavement surfaces owing to their depth penetration capabilities [72; 94]. Deep-learning algorithms have been applied to automate distress detection using GPR signals and images [68; 106]. However, as stated in [91], they are inefficient in terms of cost and benefit for surface distress detection as they can only detect cracks even though many other distresses are present. Due to the additional cost of equipment and the need to integrate it with the results of vision-based distress detection, other 3D data collection methods are more prevalent.

Finally, accurate, repeatable, and meaningful pavement condition results depend on appropriate data-gathering procedures. Therefore, it is necessary to create standardised processes to guarantee repeatability, comparability, and integration with pavement management systems.

5.4 Comparison of AI models

As mentioned earlier, YOLO was developed in 2015, and an improved version was published each year thereafter, and to date, there are 11 models. A systematic review of the studies reveals that version 5 is most commonly used for pavement distress detection, with version 8 being preferred more recently. Although the majority of articles were published in the last 5–6 years, not only recent versions but also versions from YOLOv3 have been used for pavement distress detection (Table 2). Many researchers have used multiple versions to compare the YOLO algorithms in terms of processing speed and accuracy as well as to compare YOLO algorithms with other algorithms, mainly various CNN models. Researchers have highlighted that YOLO version 8 is the most efficient one [30; 63], whereas versions 10 and 11 have yet to be fully explored. Along with testing the available basic YOLO versions, some researchers have developed their own YOLO-based algorithms with the aim of overcoming a certain shortcoming within their specific case. Thus, modified YOLO algorithms have been developed for poor visibility under low-light conditions [21; 94], front-view images with challenging backgrounds [40], small, sparse, and low-resolution pavement defects [107], and small and irregular potholes [86]. Some models have been improved in terms of shape feature detection of potholes to achieve a more accurate, real-time detection [33] or combined with an integrated laser device to measure the depth and volume of potholes and sinkholes [108]. In one case [52], the researchers have modified the YOLO algorithm to detect rutting along with commonly determined potholes and cracks. Furthermore, some YOLO algorithms have been modified for application to different road types, such as feeders and rural roads [62], or for the detection of forest road visible bodies [51]. Other enhanced models have different attention mechanisms [109] added for better efficiency or duplicate decoupling for higher accuracy [76], and other features incorporated to enhance pavement distress detection performance [74].

Table 2. YOLO application in pavement distress detection

YOLO version	Reference	Application
v11	[37]	Road damage detection
	[78]	Road damage detection with UAV aerial images
v10	[39]	Road damage detection *In complex detection scenarios and resource-constrained environments
v8	[38]	Road damage detection for autonomous vehicles
	[74; 77]	Road damage detection
v7	[73]	Crack and pothole detection *Dynamic ensemble of classification mechanisms (DynamicECM) added to YOLO to filter out false positive pothole detections
v5	[47]	Detection of large distresses from street-view images
	[41]	Autonomous vehicle detection of potholes and speed breakers
	[48; 110]	Pothole detection
	[111]	Detection and estimation of pothole dimensions and locations
	[91]	Detection and classification of defects
v4	[13; 56]	Pavement distress detection with UAV
v3	[65]	Detection and measurement of various distress types in flexible and stone road pavements
	[55]	Pothole detection
	[13; 56]	Pavement distress detection with UAV

Table 3. Comparison between different YOLO versions and other AI algorithms

Reference	AI algorithms	Findings
[56]	YOLOv3, YOLOv4, CenterNet, Faster R-CNN, and EfficientNet YOLOv3	Road defects from UAV road damage database
[57]	YOLOX and other YOLO versions	For pothole detection, YOLOX had higher accuracy and low computational cost
[58]	YOLOv3, YOLOv3-tiny, YOLOv4, YOLOv4-tiny, YOLOv5s, and YOLOv5x	For pothole detection, YOLOv4 had highest accuracy and YOLOv4-tiny had best inference time, making it suitable for mobile apps. YOLOv5 exhibited good potential due to ease of implementation.
[63]	YOLOv3, YOLOv5, YOLOv7, and YOLOv8	For pavement distress detection, YOLOv8 was most efficient
[13]	Faster R-CNN, YOLOv3, and YOLOv4	For pavement distress detection from UAV images, YOLOv3 yielded the best results albeit at a low accuracy (56 %)
[112]	Faster R-CNN, Sparse R-CNN, YOLOv3, YOLOv5, and YOLOv7	For pothole detection, YOLOv7 had the highest accuracy
[71]	Faster R-CNN, YOLOv3, YOLOv3-SPP, and YOLOv5	For pavement damage detection using CNN and infrared thermography, YOLOv5 was the most efficient and accurate
[32]	Mask-RCNN, YOLOv5, SSD, and NanoDet	YOLOv5 with LiDAR was superior for pothole detection
[85]	YOLOv5, YOLOv6, and YOLOv7	YOLOv7 showed superior efficiency for pothole detection
[44]	YOLOv5, YOLOv7, YOLOv8 + U-Net, W-segnet, and SegNet	For detection of pavement distress and dropped objects such as bottles, YOLOv8 was most suitable for region-level detection, while W-segnet was most effective for pixel-level segmentation

In addition to being used as a tool for pavement distress detection, different YOLO versions serve as benchmark tests for comparing the efficacy of other newly created algorithms [42; 87] and for testing newly formed distress datasets with the goal of being used for future model training [83]. To best serve this purpose, AI algorithms should be trained on datasets containing information on roads with properties similar to those surveyed, i.e., the type of pavement surface (paved, unpaved, stone roads, etc.). In [83], the researchers realised the need to create a new distress dataset, as distresses have certain features specific to road types, traffic, climate, and other local factors. They created a pavement distress dataset specific to distresses in Egypt, which can also be used in northern Africa and the Middle East, and verified it with YOLO algorithms.

In search for the most efficient model in terms of detection accuracy and computational time for the detection, classification, and retrieval of different information on pavement damage, researchers compared different AI models on the same datasets, as shown in Table 3. Other AI models were also tested using different YOLO versions.

When it comes comparing different YOLO versions, it is expected that the more recent the version, the better the results, as its detection possibility, classification, and computational time improve over the years. Compared with other AI models, YOLO is often advantageous in terms of detection accuracy and speed. Because of its architecture and single-stage detection, it is faster, computationally efficient, and easier to implement, and is therefore more suitable for various applications. However, when it comes to images with complex backgrounds [40], small or low-resolution distresses [107], and low-visibility conditions [94], YOLO algorithms can be modified to improve their accuracy or alternatively, other AI architectures can be used. Although YOLO algorithms are suitable for region-level detection, bounding boxes, and distress classification, one study [44] has shown that the SegNet model is superior in terms of image segmentation at the pixel level. This means that to gather information on size, area, or other distress features, more complex models with two-stage detection would be more effective, or this addition can be integrated into YOLO models, such as YOLOv8-seg [108]. This is a YOLOv8-based model with the added capability of determining the shape of an object in an image at the pixel level.

6 Conclusions

This review demonstrates that AI-driven pavement distress detection has become a rapidly expanding research field, driven by advances in deep learning and the increasing availability of image and sensor data. However, several critical issues hinder the reliable and widespread implementation of these technologies:

- Lack of systematic comparison between human and AI assessments: Only a small number of studies have directly evaluated AI models against human evaluators, and those that do typically involve a limited number of human evaluators. There is no widely accepted methodology for validating whether AI surpasses or merely approximates human inspection performance.
- Absence of standardised datasets and a unified evaluation methodology: Existing public datasets cover limited distress types and visual contexts, while most studies rely on private datasets, reducing reproducibility. No harmonised framework exists for objectively comparing different algorithms or ensuring consistency across studies.
- Insufficient development of 3D data acquisition and reconstruction techniques for lower-ranking roads: Although 3D methods are essential for identifying potholes, ruts, manholes, and surface irregularities, current approaches remain costly, technically complex, or sensitive to environmental conditions. Therefore, more robust, scalable, and low-cost 3D solutions are required.

Overall, although AI offers a strong potential to transform pavement condition assessment, especially for low-volume roads, future progress depends on establishing standardised ground-truthing procedures, creating comprehensive multi-modal datasets, and advancing reliable 3D imaging methodologies that enable accurate and repeatable condition evaluations.

Acknowledgments

This research was funded by the European Union-Next Generation EU under the project 581 UNIOS-73, Harmonization of Innovation and Intelligent Transport Infrastructure – HIPI.

References

[1] Kaseko, M. S.; Lo, Z.-P.; Ritchie, S. G. Comparison of Traditional and Neural Classifiers for Pavement-Crack Detection. *Journal of Transportation Engineering*, 1994, 120 (4), pp. 552-569. https://doi.org/10.1061/(ASCE)0733-947X(1994)120:4(552)

[2] Yoo, H.-S.; Kim, Y.-S. Development of a crack recognition algorithm from non-routed pavement images using artificial neural network and binary logistic regression. *Journal of Civil Engineering*, 2016, 20 (4), pp. 1151-1162. https://doi.org/10.1007/s12205-015-1645-9

[3] Yang, G. et al. Datasets and processing methods for boosting visual inspection of civil infrastructure: A comprehensive review and algorithm comparison for crack classification, segmentation, and detection. *Construction and Building Materials*, 2022, 356, 129226. https://doi.org/10.1016/j.conbuildmat.2022.129226

[4] Shang, J. et al. Automated pavement detection and artificial intelligence pavement image data processing technology. *Automation in Construction*, 2024, 168, 105797. https://doi.org/10.1016/j.autcon.2024.105797

[5] Tafida, A. et al. Advancing smart transportation: A review of computer vision and photogrammetry in learning-based dimensional road pavement defect detection. *Computer Science Review*, 2025, 56, 100729. https://doi.org/10.1016/j.cosrev.2025.100729

[6] Zheng, L. et al. Deep learning-based intelligent detection of pavement distress. *Automation in Construction*, 2024, 168, 105772. https://doi.org/10.1016/j.autcon.2024.105772

[7] Zhuang, H. et al. Deep learning for surface crack detection in civil engineering: A comprehensive review. *Measurement*, 2025, 248, 116908. https://doi.org/10.1016/j.measurement.2025.116908

[8] Wu, Y. et al. Deep learning in crack detection: A comprehensive scientometric review. *Journal of Infrastructure Intelligence and Resilience*, 2025, 4 (3), 100144. https://doi.org/10.1016/j.iintel.2025.100144

[9] Sholevar, N.; Golroo, A.; Esfahani, S. R. Machine learning techniques for pavement condition evaluation. *Automation in Construction*, 2022, 136, 104190. https://doi.org/10.1016/j.autcon.2022.104190

[10] Passas, I. Bibliometric Analysis: The Main Steps. *Encyclopedia*, 2024, 4 (2), pp. 1014-1025. https://doi.org/10.3390/encyclopedia4020065

[11] Öztürk, O.; Kocaman, R.; Kanbach, D. K. How to design bibliometric research: an overview and a framework proposal. *Review of Managerial Science*, 2024, 18, pp. 3333-3361. https://doi.org/10.1007/s11846-024-00738-0

[12] Aria, M.; Cuccurullo, C. *bibliometrix*: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 2017, 11 (4), pp. 959-975. https://doi.org/10.1016/j.joi.2017.08.007

[13] Zhu, J. et al. Pavement distress detection using convolutional neural networks with images captured via UAV. *Automation in Construction*, 2022, 133, 103991. https://doi.org/10.1016/j.autcon.2021.103991

[14] Majidifard, H.; Adu-Gyamfi, Y.; Buttlar, W. G. Deep machine learning approach to develop a new asphalt pavement condition index. *Construction and Building Materials*, 2020, 247, 118513. https://doi.org/10.1016/j.conbuildmat.2020.118513

[15] Murat, A. A.; Kiran, M. S. A comprehensive review on YOLO versions for object detection. *Engineering Science and Technology, an International Journal*, 2025, 70, 102161. https://doi.org/10.1016/j.jestch.2025.102161
[16] Kang, S. et al. Object Detection YOLO Algorithms and Their Industrial Applications: Overview and Comparative Analysis. *Electronics*, 2025, 14 (6), 1104. https://doi.org/10.3390/electronics14061104
[17] Tamagusko, T.; Correia, M. G.; Ferreira, A. Machine Learning Applications in Road Pavement Management: A Review, Challenges and Future Directions. *Infrastructures*, 9 (12), 213. https://doi.org/10.3390/infrastructures9120213
[18] Krichen, M. Convolutional Neural Networks: A Survey. *Computers*, 2023, 12 (8), 151. https://doi.org/10.3390/computers12080151
[19] Redmon, J. et al. You Only Look Once: Unified, Real-Time Object Detection. In: *Proceedings 299th IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. June 26- July 1, 2016, Las Vegas, USA, IEEE Computer Society; 2016, pp. 779-788. https://doi.org/10.48550/arXiv.1506.02640
[20] Nalawi, M. et al. Design of a Real-time Detection System for Potholes and Bumps Using Deep Learning. In: *22nd International Conference on Research and Education in Mechatronics (REM)*. September 24-26, 2024, Jordan, Institute of Electrical and Electronics Engineers, Inc. (IEEE); 2024, pp. 160-165. https://doi.org/10.1109/rem63063.2024.10735479
[21] Jakubec, M. et al. Pothole detection in adverse weather: leveraging synthetic images and attention-based object detection methods. *Multimedia Tools and Applications*, 2024, 83 (39), pp. 86955-86982. https://doi.org/10.1007/s11042-024-19723-6
[22] Gómez-Conti, P.; Osorio-Lird, A.; Allende-Cid, H. Automated Distress Detection, Classification and Measurement for Asphalt Urban Pavements Using YOLO. *Engineering Proceedings*, 2023, 36 (1), 58. https://doi.org/10.3390/engproc2023036058
[23] Arya, D. et al. Deep learning-based road damage detection and classification for multiple countries. *Automation in Construction*, 2021, 132, 103935. https://doi.org/10.1016/j.autcon.2021.103935
[24] Qureshi, W. S. et al. Deep learning framework for intelligent pavement condition rating: A direct classification approach for regional and local roads. *Automation in Construction*, 2023, 153, 104945. https://doi.org/10.1016/j.autcon.2023.104945
[25] Hossain, M. S.; Angan, R. B.; Hasan, M. M. Pothole Detection and Estimation of Repair Cost in Bangladeshi Street: AI-based Multiple Case Analysis. In: *2023 International Conference on Electrical, Computer and Communication Engineering (ECCE)*. February 23-25, 2023, Chittagong, Bangladesh, Institute of Electrical and Electronics Engineers, Inc. (IEEE), 2023, pp. 1-6. https://doi.org/10.1109/ecce57851.2023.10101579
[26] Amo-Boateng, M.; Adu-Gyamfi, Y. Generative adversarial network for real-time identification and pixel-level annotation of highway pavement distresses. *Automation in Construction*, 2025, 174, 106122. https://doi.org/10.1016/j.autcon.2025.106122
[27] Nguyen, S. D. et al. DEPP: Automated detection of pavement patching and nonslip coatings. *Measurement*, 2025, 252, 117315. https://doi.org/10.1016/j.measurement.2025.117315
[28] Gayathri, K.; Thangavelu, S. Novel deep learning model for vehicle and pothole detection. *Indonesian Journal of Electrical Engineering and Computer Science*, 2021, 23 (3), pp. 1576-1582. https://doi.org/10.11591/ijeecs.v23.i3.pp1576-1582
[29] Gökçe, B.; Sonugür, G. Recognition of dynamic objects from UGVs using Interconnected Neural network-based Computer Vision system. *Automatika*, 2022, 63 (2), pp. 244-258. https://doi.org/10.1080/00051144.2022.2031539
[30] Khan, M. et al. Pothole detection for autonomous vehicles using deep learning: a robust and efficient solution. *Frontiers in Built Environment*, 2024, 9. https://doi.org/10.3389/fbuil.2023.1323792

[31] Bala, J. A.; Adeshina, S. A.; Aibinu, A. M. Performance Evaluation of You Only Look Once v4 in Road Anomaly Detection and Visual Simultaneous Localisation and Mapping for Autonomous Vehicles. *World Electric Vehicle Journal*, 2023, 14 (9), 265. https://doi.org/10.3390/wevj14090265

[32] Thomas, A. et al. A novel road attribute detection system for autonomous vehicles using sensor fusion. *International Journal of Information Technology*, 2024, 17 (1), pp. 161-168. https://doi.org/10.1007/s41870-024-02255-5

[33] Tang, P. et al. Pothole detection-you only look once: Deformable convolution based road pothole detection. *IET Image Processing*, 2024, 19 (1), e13300. https://doi.org/10.1049/ipr2.13300

[34] Kortmann, F. et al. Watch out, pothole! featuring road damage detection in an end-to-end system for autonomous driving. *Data & Knowledge Engineering*, 2022, 142, 102091. https://doi.org/10.1016/j.datak.2022.102091

[35] Swain, S.; Tripathy, A. K. Automatic detection of potholes using VGG-16 pre-trained network and Convolutional Neural Network. *Heliyon*, 2024, 10 (10), e30957. https://doi.org/10.1016/j.heliyon.2024.e30957

[36] Zhao, Y. et al. Crack instance segmentation using splittable transformer and position coordinates. *Automation in Construction*, 2024, 168 (Part B), 105838. https://doi.org/10.1016/j.autcon.2024.105838

[37] Liu, X.; Liu, Y.; Luo, P. A YOLOv11 Empowered Road Defect Detection Model. *Computers, Materials & Continua*, 2025, 85 (1), pp. 1073-1094. https://doi.org/10.32604/cmc.2025.066078

[38] Sattar, K. A. et al. Detecting Road Defects and Hazards in Metropolitan Environments Using Optimized Deep Learning Techniques. *Transportation Research Procedia*, 2025, 84, pp. 528-533. https://doi.org/10.1016/j.trpro.2025.03.105

[39] Ou, J. et al. An improved YOLOv10-based lightweight multi-scale feature fusion model for road defect detection and its applications. *Advances in Engineering Software*, 2025, 208, 103976. https://doi.org/10.1016/j.advengsoft.2025.103976

[40] Li, J. et al. A method of road damage detection for complex background images based on region guidance network. *Pattern Recognition*, 2025, 168, 111780. https://doi.org/10.1016/j.patcog.2025.111780

[41] Nissimagoudar, P. C. et al. Detection of Potholes and Speed Breaker for Autonomous Vehicles. *Procedia Computer Science*, 2024, 237 pp. 675-682. https://doi.org/10.1016/j.procs.2024.05.153

[42] Bouhsissin, S.; Assemlali, H.; Sael, N. Enhancing road safety: A convolutional neural network based approach for road damage detection. *Machine Learning with Applications*, 2025, 20, 100668. https://doi.org/10.1016/j.mlwa.2025.100668

[43] Bhavana, N. et al. POT-YOLO: Real-Time Road Potholes Detection Using Edge Segmentation-Based Yolo V8 Network. *IEEE Sensors Journal*, 2024, 24 (15), pp. 24802-24809. https://doi.org/10.1109/jsen.2024.3399008

[44] Xu, L. et al. Automatic Detection of Urban Pavement Distress and Dropped Objects with a Comprehensive Dataset Collected via Smartphone. *Buildings*, 2024, 14 (6), 1546. https://doi.org/10.3390/buildings14061546

[45] Gorro, K. D. et al. Pothole Detection: A Study of Ensemble Learning and Decision Framework. *International Journal of Advanced Computer Science and Applications*, 2025, 16 (4), pp. 67-79. http://dx.doi.org/10.14569/IJACSA.2025.0160408

[46] He, T.; Wang, C., Lan, R., Luo, H. Research on highway road condition intelligent assessment and optimization system based on deep learning and internet of things. *Systems and Soft Computing*, 2025, 7, 200361. https://doi.org/10.1016/j.sasc.2025.200361

[47] Ren, M. et al. YOLOv5s-M: A deep learning network model for road pavement damage detection from urban street-view imagery. *International Journal of Applied Earth Observation and Geoinformation*, 2023, 120, 103335. https://doi.org/10.1016/j.jag.2023.103335

[48] Palwe, S. et al. An Intelligent and Deep Learning Approach for Pothole Surveillance Smart Application. *Procedia Computer Science*, 2024, 235, pp. 3271-3282. https://doi.org/10.1016/j.procs.2024.04.309
[49] Sharma, Y.; Durga, Y. J.; Chellamani, G. K. Real-Time Detection of Potholes and Speed Breakers for Enhanced Road Safety. *Procedia Computer Science*, 2025, 260, pp. 888-897. https://doi.org/10.1016/j.procs.2025.03.271
[50] Saisree, C.; Kumaran, U. Pothole Detection Using Deep Learning Classification Method. *Procedia Computer Science*, 2023, 218, pp. 2143-2152. https://doi.org/10.1016/j.procs.2023.01.190
[51] Hoseini, M. et al. RoadSens: An integrated near-field sensor solution for 3D forest road monitoring. *Computers and Electronics in Agriculture*, 2025, 229, 109710. https://doi.org/10.1016/j.compag.2024.109710
[52] Jiang, T.-Y.; Liu, Z.-Y.; Zhang, G.-Z. YOLOv5s-road: Road surface defect detection under engineering environments based on CNN-transformer and adaptively spatial feature fusion. *Measurement*, 2025, 242 (Part B), 115990. https://doi.org/10.1016/j.measurement.2024.115990
[53] Wang, H. et al. A customized multi-class pavement distress segmentation method for routine repair monitoring. *Engineering Applications of Artificial Intelligence*, 2025, 154, 111002. https://doi.org/10.1016/j.engappai.2025.111002
[54] Sathya, R.; Saleena, B. CNN-MAO: Convolutional Neural Network-based Modified Aquilla Optimization Algorithm for Pothole Identification from Thermal Images. *Signal, Image and Video Processing*, 2022, 16 (8), pp. 2239-2247. https://doi.org/10.1007/s11760-022-02189-0
[55] Anandhalli, M. et al. Indian pothole detection based on CNN and anchor-based deep learning method. *International Journal of Information Technology*, 2022, 14 (7), pp. 3343-3353. https://doi.org/10.1007/s41870-022-00881-5
[56] Zhang, Y. et al. Road damage detection using UAV images based on multi-level attention mechanism. *Automation in Construction*, 2022, 144, 104613. https://doi.org/10.1016/j.autcon.2022.104613
[57] Mohan Prakash, B.; Sriharipriya, K. C. Enhanced pothole detection system using YOLOX algorithm. *Autonomous Intelligent Systems*, 2022, 2 (1), 22. https://doi.org/10.1007/s43684-022-00037-z
[58] Tamagusko, T.; Ferreira, A. Optimizing Pothole Detection in Pavements: A Comparative Analysis of Deep Learning Models. *Engineering Proceedings*, 36 (1), 11. https://doi.org/10.3390/engproc2023036011
[59] Benallal, M. A.; Tayeb, M. S. An image-based convolutional neural network system for road defects detection. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 2023, 12 (2), pp. 577-584. https://doi.org/10.11591/ijai.v12.i2.pp577-584
[60] Zhang, Y.; Liu, C. Real-Time Pavement Damage Detection With Damage Shape Adaptation. *IEEE Transactions on Intelligent Transportation Systems*, 2024, 25 (11), pp. 18954-18963. https://doi.org/10.1109/tits.2024.3416508
[61] Tsung, C.-K. et al. HPPH: Computer-Vision-Based Service for High-Performance Pavement Health Recognition. *IEEE Internet of Things Journal*, 2025, 12 (11), pp. 15987-15996. https://doi.org/10.1109/jiot.2025.3530253
[62] Fan, Y. et al. Disease Monitoring and Characterization of Feeder Road Network Based on Improved YOLOv11. *Electronics*, 2025, 14 (9), 1818. https://doi.org/10.3390/electronics14091818
[63] Manjusha, M.; Sunitha, V. Optimizing YOLO models for high-accuracy automated detection and classification of road surface distresses. *Innovative Infrastructure Solutions*, 2025, 10 (8), 381. https://doi.org/10.1007/s41062-025-02191-8
[64] Luo, S. et al. EPDD-YOLO: An efficient benchmark for pavement damage detection based on Mamba-YOLO. *Measurement*, 2025, 253 (Part C), 117638. https://doi.org/10.1016/j.measurement.2025.117638

[65] Guerrieri, M.; Parla, G. Flexible and stone pavements distress detection and measurement by deep learning and low-cost detection devices. *Engineering Failure Analysis*, 2022, 141, 106714. https://doi.org/10.1016/j.engfailanal.2022.106714
[66] Yoon, S.; Cho, J. Convergence of Stereo Vision-Based Multimodal YOLOs for Faster Detection of Potholes. *Computers, Materials & Continua*, 2022, 73 (2), pp. 2821-2834. https://doi.org/10.32604/cmc.2022.027840
[67] Li, D. et al. Automated classification and detection of multiple pavement distress images based on deep learning. *Journal of Traffic and Transportation Engineering (English Edition)*, 2023, 10 (2), pp. 276-290. https://doi.org/10.1016/j.jtte.2021.04.008
[68] El Hakea, A. H.; Fakhr, M. W. Recent computer vision applications for pavement distress and condition assessment. *Automation in Construction*, 2023, 146, 104664. https://doi.org/10.1016/j.autcon.2022.104664
[69] Li, J.; Yuan, C.; Wang, X. Real-time instance-level detection of asphalt pavement distress combining space-to-depth (SPD) YOLO and omni-scale network (OSNet). *Automation in Construction*, 2023, 155, 105062. https://doi.org/10.1016/j.autcon.2023.105062
[70] Wu, P.; Wu, J.; Xie, L. Pavement distress detection based on improved feature fusion network. *Measurement*, 2024, 236, 115119. https://doi.org/10.1016/j.measurement.2024.115119
[71] Liu, F. et al. Multiple-type distress detection in asphalt concrete pavement using infrared thermography and deep learning. *Automation in Construction*, 2024, 161, 105355. https://doi.org/10.1016/j.autcon.2024.105355
[72] Zhang, A. A. et al. Intelligent pavement condition survey: Overview of current researches and practices. *Journal of Road Engineering*, 2024, 4 (3), pp. 257-281. https://doi.org/10.1016/j.jreng.2024.04.003
[73] Bekku, H. et al. A stable and efficient dynamic ensemble method for pothole detection. *Pervasive and Mobile Computing*, 2024, 104, 101973. https://doi.org/10.1016/j.pmcj.2024.101973
[74] Chen, W. et al. Road surface damage detection based on enhanced YOLOv8. *Computers in Industry*, 2025, 173, 104363. https://doi.org/10.1016/j.compind.2025.104363
[75] Zhou, J.; Wang, Y.; Zhou, W. Efficient instance segmentation framework for UAV-based pavement distress detection. *Automation in Construction*, 2025, 175, 106195. https://doi.org/10.1016/j.autcon.2025.106195
[76] Liu, Y. et al. A non-destructive automatic pavement damage detection scheme based on end-to-end neural networks with multi-level attention mechanism. *Engineering Applications of Artificial Intelligence*, 2025, 156, 111246. https://doi.org/10.1016/j.engappai.2025.111246
[77] Yang, J. S.; Chen, W.; Xiao, X. Pavement damage detection with a novel semi-supervised YOLOv8 network. *Measurement*, 2026, 257, 118860. https://doi.org/10.1016/j.measurement.2025.118860
[78] Li, H. et al. An automatic detection method for road damage in UAV images based on multi-level perception and feature aggregation. *Advanced Engineering Informatics*, 2026, 69 (Part A), 103814. https://doi.org/10.1016/j.aei.2025.103814
[79] Alatoom, Y. I.; Smadi, O. Embedded framework for low-cost pavement condition evaluation using microcontroller and single-board computer platforms. *Automation in Construction*, 2025, 178, 106442. https://doi.org/10.1016/j.autcon.2025.106442
[80] Sun, P. et al. DSWMamba: A deep feature fusion mamba network for detection of asphalt pavement distress. *Construction and Building Materials*, 2025, 469, 140393. https://doi.org/10.1016/j.conbuildmat.2025.140393
[81] Chougule, S.; Barhatte, A. Smart Pothole Detection System using Deep Learning Algorithms. *International Journal of Intelligent Transportation Systems Research*, 2023, 21 (3), pp. 483-492. https://doi.org/10.1007/s13177-023-00363-3

[82] Youwai, S.; Chaiyaphat, A.; Chaipetch, P. YOLO9tr: a lightweight model for pavement damage detection utilizing a generalized efficient layer aggregation network and attention mechanism. *Journal of Real-Time Image Processing*, 2024, 21 (5), 163. https://doi.org/10.1007/s11554-024-01545-2

[83] Abdelkader, M. F. et al. EGY_PDD: a comprehensive multi-sensor benchmark dataset for accurate pavement distress detection and classification. *Multimedia Tools and Applications*, 2025, 84 (31), pp. 38509-38544. https://doi.org/10.1007/s11042-025-20700-w

[84] Talha, S. A. et al. A LiDAR-camera fusion approach for automated detection and assessment of potholes using an autonomous vehicle platform. *Innovative Infrastructure Solutions*, 2023, 8 (10), 274. https://doi.org/10.1007/s41062-023-01232-4

[85] Omar, M.; Kumar, P. PD-ITS: Pothole Detection Using YOLO Variants for Intelligent Transport System. *SN Computer Science*, 2024, 5 (5), 552. https://doi.org/10.1007/s42979-024-02887-1

[86] Rubin, R. et al. Pothole Detection and Assessment on Highways Using Enhanced YOLO Algorithm With Attention Mechanisms. *Advances in Civil Engineering*, 2025, 2025 (1), 7911336. https://doi.org/10.1155/adce/7911336

[87] Xing, H. et al. Enhanced end-to-end regression algorithm for autonomous road damage detection. *The Journal of Supercomputing*, 2025, 81 (2), 380. https://doi.org/10.1007/s11227-024-06871-7

[88] Abdelwahed, S. H. et al. Advancements in real-time road damage detection: a comprehensive survey of methodologies and datasets. *Journal of Real-Time Image Processing*, 2025, 22 (4), 137. https://doi.org/10.1007/s11554-025-01683-1

[89] Vinodhini, K. A.; Sidhaarth, K. R. A. Pothole detection in bituminous road using CNN with transfer learning. *Measurement: Sensors*, 2024, 31, 100940. https://doi.org/10.1016/j.measen.2023.100940

[90] Chu, H.-H. et al. Deep Learning Method to Detect the Road Cracks and Potholes for Smart Cities. *Computers, Materials & Continua*, 2023, 75 (1), pp. 1863-1881. https://doi.org/10.32604/cmc.2023.035287

[91] Kaya, Ö.; Çodur, M. Y. Automatic detection and classification of road defects on a global-scale: Embedded system. *Measurement*, 2025, 243, 116453. https://doi.org/10.1016/j.measurement.2024.116453

[92] Yu, H. et al. Advances and innovations in road surface inspection with light detection and ranging technology. *Journal of Industrial Information Integration*, 2025, 45, 100842. https://doi.org/10.1016/j.jii.2025.100842

[93] Paramarthalingam, A. et al. A deep learning model to assist visually impaired in pothole detection using computer vision. *Decision Analytics Journal*, 2024, 12, 100507. https://doi.org/10.1016/j.dajour.2024.100507

[94] Xu, X. et al. Enhanced pothole detection in low-light conditions using DCE-Pothole and YOLOv10 fusion. *Results in Engineering*, 2025, 28, 107322. https://doi.org/10.1016/j.rineng.2025.107322

[95] Zhong, J. et al. A novel method for pothole detection based on incomplete point clouds. *Measurement*, 2025, 252, 117344. https://doi.org/10.1016/j.measurement.2025.117344

[96] Dib, J.; Sirlantzis, K.; Howells, G. Application of Deep Learning Techniques in Negative Road Anomalies Detection. In: *Proceedings of the 14th International Joint Conference on Computational Intelligence*, Bäck, T. et al. (eds.). October 24-26, 2022, Valletta, Malta, Scitepress, 2022, pp. 475-482. https://doi.org/10.5220/0011336000003332

[97] Ejaz, N.; Alam, A. B. M. B.; Choudhury, S. Generative AI-driven edge-cloud system for intelligent road infrastructure inspection. *Results in Engineering*, 2025, 27, 105844. https://doi.org/10.1016/j.rineng.2025.105844

[98] Jing, J. et al. Self-adaptive 2D–3D image fusion for automated pixel-level pavement crack detection. *Automation in Construction*, 2024, 168 (Part A), 105756. https://doi.org/10.1016/j.autcon.2024.105756
[99] Bosurgi, G. et al. An automatic pothole detection algorithm using pavement 3D data. *International Journal of Pavement Engineering*, 2023, 24 (2), 2057978. https://doi.org/10.1080/10298436.2022.2057978
[100] Weng, Z. et al. Pavement texture depth estimation using image-based multiscale features. *Automation in Construction*, 2022, 141, 104404. https://doi.org/10.1016/j.autcon.2022.104404
[101] Li, J.; Liu, T.; Wang, X. Advanced pavement distress recognition and 3D reconstruction by using GA-DenseNet and binocular stereo vision. *Measurement*, 2022, 201, 111760. https://doi.org/10.1016/j.measurement.2022.111760
[102] Guan, J. et al. Automated pixel-level pavement distress detection based on stereo vision and deep learning. *Automation in Construction*, 2021, 129, 103788. https://doi.org/10.1016/j.autcon.2021.103788
[103] Liu, Y. et al. Extraction of rutting features in asphalt pavements using airborne laser scanning. *Automation in Construction*, 2026, 181, 106646. https://doi.org/10.1016/j.autcon.2025.106646
[104] Dan, H.-C.; Lu, B.; Li, M. Evaluation of asphalt pavement texture using multiview stereo reconstruction based on deep learning. *Construction and Building Materials*, 2024, 412, 134837. https://doi.org/10.1016/j.conbuildmat.2023.134837
[105] Mahmoudzadeh, A. et al. Estimating Pavement Roughness by Fusing Color and Depth Data Obtained from an Inexpensive RGB-D Sensor. *Sensors*, 2019, 19 (7), 1655. https://doi.org/10.3390/s19071655
[106] Yang, X. et al. Research and applications of artificial neural network in pavement engineering: A state-of-the-art review. *Journal of Traffic and Transportation Engineering (English Edition)*, 2021, 8 (6), pp. 1000-1021. https://doi.org/10.1016/j.jtte.2021.03.005
[107] Li, Z. et al. MGD-YOLO: An Enhanced Road Defect Detection Algorithm Based on Multi-Scale Attention Feature Fusion. *Computers, Materials & Continua*, 2025, 84 (3), pp. 5613-5635. https://doi.org/10.32604/cmc.2025.066188
[108] Park, S.-S.; Nguyen, N.-N. Two-camera vision technique for measuring pothole area and depth. *Measurement*, 2025, 247, 116809. https://doi.org/10.1016/j.measurement.2025.116809
[109] Yao, H. et al. Development and optimization of object detection technology in pavement engineering: A literature review. *Journal of Road Engineering*, 2024, 4 (2), pp. 163-188. https://doi.org/10.1016/j.jreng.2024.01.006
[110] Klco, P. et al. Automated Detection Of Potholes Using YOLOv5 Neural Network. *Transportation Research Procedia*, 2023, 74, pp. 1150-1155. https://doi.org/10.1016/j.trpro.2023.11.255
[111] Ruseruka, C. et al. Augmenting roadway safety with machine learning and deep learning: Pothole detection and dimension estimation using in-vehicle technologies. *Machine Learning with Applications*, 2024, 16, 100547. https://doi.org/10.1016/j.mlwa.2024.100547
[112] Lieskovská, E. et al. Automatic pothole detection. *Transportation Research Procedia*, 2023, 74, pp. 1164-1170. https://doi.org/10.1016/j.trpro.2023.11.257