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Machine learning-based pavement crack detection, classification, and characterization: a review

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ABSTRACT

The detection, classification, and characterization of pavement cracks are critical for maintaining safe road conditions. However, traditional manual inspection methods are slow, costly, and pose risks to inspectors. To address these issues, this article provides a comprehensive overview of state-of-the-art machine vision and machine learning-based techniques for pavement crack detection, classification, and characterization. The paper explores the process flow of these systems, including both machine learning and traditional methodologies. The paper focuses on popular artificial intelligence (AI) techniques like support vector machines (SVM) and neural networks. It underscores the significance of utilizing image processing methods for feature extraction in order to detect cracks. The paper also discusses significant advancements made through deep learning strategies. The main objectives of this research are to improve efficiency and effectiveness in pavement crack detection, reduce inspection costs, and enhance safety. Additionally, the article presents data gathering approaches, various datasets for developing road crack detection models, and compares different models to demonstrate their advantages and limitations. Finally, the paper identifies open challenges in the field and provides valuable insights for future research and development efforts. Overall, this paper highlights the potential of AI-based techniques to revolutionize pavement maintenance practices and significantly improve road safety.

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1. INTRODUCTION

The integrity and performance of pavement are heavily influenced by road disintegration, which can lead to various damages requiring timely detection and characterization for effective maintenance [1]. Road cracks are among the primary factors contributing to road damage, as they not only degrade the road appearance and driving comfort, but can also progress to cause structural damage and reduce the pavement's lifespan [2]. With the increasing traffic on roads, the importance of pavement maintenance has gained significant attention. Therefore, early identification of cracks and timely repairs can mitigate the financial costs of road repairs and enhance the safety of vehicles and drivers on the road.

Traditionally, pavement crack detection and maintenance heavily relied on manual procedures, such as visual inspection by trained personnel or using handheld devices, who would visually identify and classify road cracks based on their size, shape, and severity. However, these manual methods had several limitations, including low accuracy, subjectivity, and inconsistency in results due to human factors, such as fatigue and bias. Moreover, they were time-consuming, labor-intensive, and safety-related issues [3]. These methods also required significant expertise and training, adding to the challenges of pavement maintenance. To overcome these limitations, researchers and practitioners have explored various automated techniques for pavement crack detection in the past. Some of the earlier techniques for pavement crack detection include edge detection, thresholding, and texture analysis. For instance, edge detection techniques, such as Sobel, Canny, and Roberts operators, were used to identify edges or boundaries of cracks based on changes in intensity or color. Thresholding techniques involved setting a specific intensity or color threshold to segment cracks from pavement images. Texture analysis techniques, such as Gabor filters, wavelet transforms, and local binary patterns (LBP), were used to extract textural features from pavement images for crack detection. While these earlier techniques provided some level of automation in crack detection, they had several limitations. For example, edge detection and thresholding techniques often suffered from high false positive and false negative rates due to noise, lighting conditions, and variability in crack characteristics. Texture analysis techniques, on the other hand, were limited by their ability to capture complex crack patterns and textures accurately. Moreover, these techniques relied heavily on handcrafted features, which were not always robust and adaptive to different pavement conditions and crack types. However, with the recent advancements in artificial intelligence (AI) and machine learning, machine vision-based techniques have gained popularity in the field of pavement crack detection and classification [4], [5]. In recent years, machine vision and machine learning-based techniques have emerged as promising approaches for pavement crack detection, classification, and characterization, offering improved accuracy, efficiency, and productivity [6], [7]. These techniques leverage the advancements in AI and deep learning algorithms to automatically identify and categorize road cracks from pavement images or videos, providing valuable insights for pavement management and maintenance strategies.

This paper aims to provide a comprehensive insight into machine vision and machine learning-based techniques for pavement crack detection, classification, and characterization. It will review the state-of-the-art approaches proposed or used in this field, including various stages such as data acquisition, image pre-processing, segmentation, and object detection. The paper will also discuss the strengths and limitations of different models proposed by researchers and compare their performance based on relevant parameters. Furthermore, the paper will highlight the challenges that still need to be addressed in the field of pavement crack detection and classification. Considering the importance of data availability in AI model development, this paper will also review different data collection strategies and provide a representational description of various available crack detection datasets. By providing a comprehensive overview of the current research in this area, this paper aims to contribute to the understanding of machine vision and machine learning-based techniques for pavement crack detection, classification, characterization, and highlight the potential of these approaches in improving the efficiency and effectiveness of pavement maintenance practices [8].

The paper is structured into four main sections, in which remaining sections include method, results and discussion, and conclusion. The method section describes different types of road cracks and presents the generalized system for road crack detection and classification. The results and discussion section compares different crack detection and classification models based on performance parameters and identifies open challenges in the field. The conclusion section summarizes the key findings of the review which winds up this paper.

2. METHOD

2.1. Introduction

Pavement cracks cause different road surface problems, most of which occur on the road's outer layer. Pavement damage begins when pavements age and are subjected to traffic loads. Damages can also worsen with time. For example, a crack might allow water to seep into the road, creating a pothole. Additionally, any damage is a disturbance to the pavement users and can be potentially dangerous if disregarded as their condition generally deteriorates with time. Appropriate and timely road maintenance is crucial to extend the life of the road and lessen the maintenance and repair costs. Few attributes are surveyed in roads. However, they usually are arranged in terms of surface qualities (counting longitudinal profile and harshness), asphalt damages, primary assessment, and sub-surface grades. No universal approach is observed and each road organization has its own guideline for gathering pavement condition data [9]. Hence, there are many different approaches to deciding the outcome of a similar problem [10].

Pavement cracks can lead to various road surface issues, especially on the outer layer of the road. As pavements age and endure traffic loads, they are prone to damage. Over time, these damages can worsen, for instance, cracks can allow water to penetrate into the road, resulting in potholes. Such damage not only disrupts the smoothness of the pavement, but they can also pose a potential danger to road users if left unaddressed, as the condition of the road tends to deteriorate with time. To mitigate these problems, timely and appropriate road maintenance is crucial. It helps to extend the lifespan of the road and reduce the overall costs associated with maintenance and repairs. Road maintenance assessments typically include several attributes, such as surface qualities (including longitudinal profile and roughness), asphalt damages, primary assessment, and sub-surface grades. However, it's important to note that there is no universal approach to assessing pavement conditions, as different road organizations may have their own guidelines for collecting pavement condition data [9].

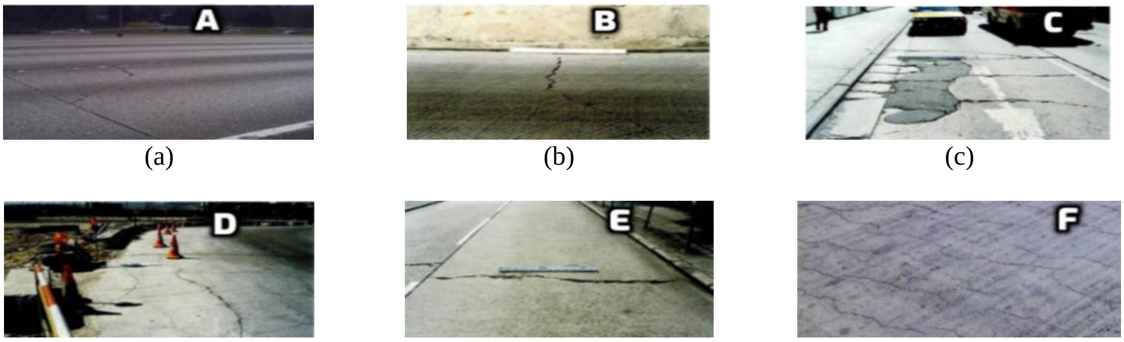
As a result, there are diverse approaches to determining the severity of pavement problems. It's imperative for road authorities to implement effective strategies for pavement maintenance, considering the unique conditions of their roads and utilizing appropriate methods to collect accurate and reliable data on pavement conditions [10]. By doing so, road authorities can make informed decisions, take proactive measures to address pavement cracks and other damages, and ensuring safe and smooth roads for all users.

2.2. Types of pavement cracks

Pavements are categorized into concrete and bituminous types, both of which are prone to cracks. It is crucial to determine the type of crack in a pavement to apply the appropriate restoration approach. Concrete cracks are caused by drying shrinkage, temperature changes, and heavy traffic, while bituminous cracks are caused by aging, oxidation, and traffic loading. The restoration approach may vary depending on the type of pavement and the severity and extent of the cracks, and proper identification of the crack type and severity can lead to cost-effective and efficient pavement restoration, prolonging its service life.

2.2.1. Concrete pavement cracks

A concrete road, also known as a rigid road, refers to a substantial layer that comes into direct contact with traffic and is used for various purposes and applications. Concrete pavements can develop different types of cracks, including corner, diagonal, block, longitudinal, transverse, and shrinkage cracks, as illustrated in Figures 1(a)-(f) respectively. Corner cracks are cracks that originate from the corner of the pavement slab and intersect the joints at a distance that is equal to or less than half the length of the slab on both sides. Diagonal cracks are cracks that do not follow a specific direction and they do not cross over or run longitudinally along the borders of inlets. Block cracks are a pattern of interconnected cracks that form rectangular squares and are uniformly distributed across the entire asphalt surface. Longitudinal cracks are cracks that are disconnected and run lengthwise along the pavement surface. Transverse cracks are cracks that run perpendicular to the direction of the road. Shrinkage cracks are short and diagonal in nature and typically do not extend all the way to the edges of the pavement.



(a) (b) (c)

(d) (e) (f)

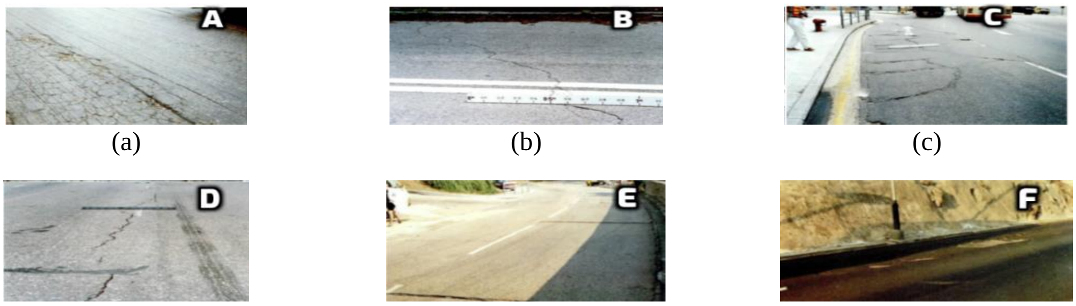
Figure 1. Types of concrete pavement cracks [11]: (a) corner cracks, (b) diagonal cracks, (c) block cracks, (d) longitudinal cracks, (e) transverse cracks, and (f) shrinkage cracks

2.2.2. Bituminous pavement cracks

Bituminous pavements are composed of a surface layer that consists of asphalt-like materials. Asphalt, a thick and sticky black liquid, is typically obtained from natural deposits such as crude petroleum. The major types of cracks commonly associated with bituminous pavements include crocodile, diagonal, block, longitudinal, transverse, and slippage cracks, as depicted in Figures 2(a)-(f) respectively.

Crocodile cracks are interconnected or intertwined cracks that form a series of small polygons resembling the skin of a crocodile. Diagonal cracks are individual cracks that extend diagonally from one corner of the pavement to another. Block cracks are interconnected cracks that form a pattern of large cells.

Longitudinal cracks are cracks that run parallel to the direction of the road. Transverse cracks are single, unrelated cracks that travel perpendicularly across the surface of the pavement. Slippage cracks are crescent-shaped cracks that point away from the direction of traffic.



(a) (b) (c)

(d) (e) (f)

Figure 2. Types of bituminous pavement cracks [11]: (a) crocodile cracks, (b) diagonal cracks, (c) block cracks, (d) longitudinal cracks, (e) transverse cracks, and (f) slippage cracks

2.3. Pavement crack parameters

Improving pavement condition analysis can be achieved through automated crack extent and severity assessment, utilizing crack characteristics such as length, width, area, and depth [12]. The evaluation parameters for pavement cracks are largely determined by the type of crack being assessed. For longitudinal and transverse cracks, crack length is commonly used as the evaluation parameter, while block and alligator cracks are assessed based on the area of the crack.

In the past, manual measurement tools such as strings, graded scales, and crack comparators were used by inspectors for crack assessment. However, these methods had limitations in terms of low precision, traceability, subjectivity in readings, and challenges in data documentation [13]. Another tool that was used to achieve higher resolution was the digital pachymeter, which required technicians to select and insert a metallic blade into the crack opening. However, manual positioning during measurement was subjective and there were uncertainties associated with the technician's handling of the device. Moreover, obtaining precise measurements required repetitive measures, which was not always practical in terms of cost, time, and labor [14].

Advancements in image processing, machine vision, and machine learning-based techniques have the potential to address these limitations and enable more precise and automated measurements of crack parameters. These technologies can provide more accurate and consistent results, eliminating the subjectivity associated with manual measurements. With automation, measurements can be obtained in a faster, more efficient manner, as well as reducing the time and labor required for crack assessment. Additionally, automated techniques can provide better traceability and documentation of data, leading to more reliable and comprehensive pavement condition analysis. By utilizing automated crack assessment techniques, pavement condition analysis can be improved, allowing for better decision-making in terms of maintenance and repair strategies. These advancements have the potential to enhance the efficiency and effectiveness of pavement management practices, leading to improved road conditions and increased road safety.

2.4. Pavement crack detection, classification, and characterization system

With the advancements in computational power, image processing, and machine learning techniques, researchers have made significant progress in the field of pavement crack detection, classification, and characterization. While different researchers may have their own methods and workflows, the basic structure for building an image processing and machine learning-based crack identification and classification system remains consistent. When these modules are combined effectively, a comprehensive system for detecting, classifying, and characterizing pavement cracks can be achieved.

As depicted in Figure 3, the crack detection, classification, and characterization system can be divided into several stages. The first step is obtaining the input data, which can be represented by images, videos or sensor data. Many researchers utilize existing databases to construct their systems, while others create their own datasets for their investigations. Data can be collected using various devices such as cell phones, cameras, satellite imaging, laser images, and sensors to create a dataset for analysis.

Once the input data is acquired, pre-processing is performed to prepare it for further analysis. Image processing techniques are applied to the images/videos, which may include operations such as cropping, resizing, histogram equalization, and color correction, depending on the specific requirements of the study.

This pre-processing stage results in clean and processed data, which is then subjected to a crack detection and classification algorithm.

It is important to note that the choice of image processing operations and techniques may vary depending on the specific research objectives and the characteristics of the pavement cracks being analyzed. Researchers need to carefully select and justify the image processing techniques used in their workflow to ensure the accuracy and reliability of the crack detection and classification results. The development of an image processing and machine learning-based system for pavement crack detection, classification, and characterization involves several stages, including obtaining input data, pre-processing, and applying crack detection and classification algorithms.

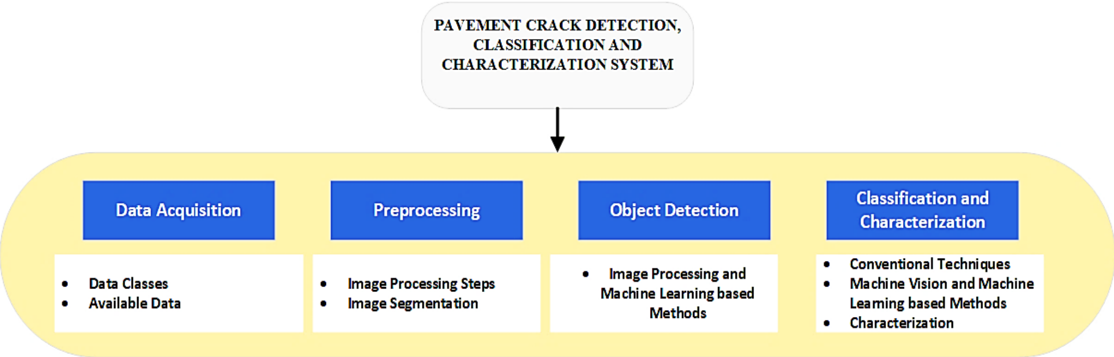


Figure 3. General pavement crack detection, classification, and characterization system

2.4.1. Crack data acquisition

Data is a fundamental asset that controls the data economy in the way oil has powered the modern economy. Therefore, data acquisition is essential for developing any machine learning model. The productivity of any machine learning model depends majorly upon the training data incorporated for the development [15], [16]. In the case of developing pavement crack detection and characterization system, the data used for training the machine learning algorithm must be exclusive and significant. The data used by several researchers for developing road crack detection systems using machine learning has been in the form of images or videos. This section reviews various image acquisition data classes associated with road cracks.

a. Crack data image classes

Crack images are classified into six categories based on their appearance in various scholarly works. Different classes of images have been shown in Table 1. Combining at least two image data classes is advantageous for crack identification and evaluation. Fusing images from many sources and utilizing the data is promising to create a more generalized, precise, and comprehensive image display for extricating scenes. The combination offers a plethora of applications.

Table 1. Image class types

Image type	Applicability
Notable light pictures	These photographs are taken using magnification equipment, surface and ground cameras, satellites, aircraft, and they have exceptional quality
Laser based	Employed mostly for image processing and the analysis of 3D fractures with average diameters from a few millimeters to several meters
CT based	They are employed to examine microscopic cracks in a research facility, with the cracks ranging in size from micrometres to millimetres
Radar images	They are used to determine fractures' depth and prepare satellite photos
Ultrasonic images	They are used for wavelet and curvelet transformations
Infrared images	They are used to determine the depth of cracks in unusual events

b. Pavement crack datasets

The performance of a machine learning model is highly dependent upon the data involved in developing the system. Hence selecting an appropriate database is highly essential [17]. Machine learning calculations cannot be fit and assessed on raw information. It should be transformed to meet the prerequisites of individual machine learning calculations. A number of pavement crack datasets have been employed by researchers for the development of road crack detection and classification models. Table 2 presents a list of available datasets incorporated into this framework.

Table 2. Pavement crack databases

No.	Database	Number of samples (images)	Resolution (pixels)	Type	Augmentation
1	Concrete crack images for classification [18]	40,000	227×227	RGB	Not present
2	RDD2020: an image dataset for smartphone-based road damage detection and classification [19]	26,336	600×600	RGB	Not present
3	Asphalt crack dataset [20]	400	448×448	RGB	Not present
4	EdmCrack600: a pixel-level annotated dataset for crack identification [21]	600	256×256	RGB	Not present
5	Crack detection: image classification	15,168	N/A	RGB	Not present
6	Cracks-and-potholes-in-road-images-dataset [22]	2,235	2,560×1,440	RGB	Not present
7	CFD [23]	118	320×480	RGB	Not present
8	AigleRN database [24]	38	N/A	Grey level	Not present
9	CRACK500	500	2,000×1,500	RGB	Present
10	German asphalt pavement distress (GAPs) dataset [25]	1,969	1,920×1,080	Grey level	Not present
11	Cracktree200 [8]	206	800×600	RGB	Not present

2.4.2. Image pre-processing

Image pre-processing is an essential step in formatting images before they are used for training and inference in object detection models. This step involves various operations such as scaling, orienting, cropping, histogram equalization, and color corrections to enhance the quality and consistency of the input data. One commonly used technique in image pre-processing is histogram equalization, which is utilized to adjust the contrast of an image. This method works by redistributing the intensity values in the image, resulting in improved overall distinction, particularly in images with low-intensity illumination [26].

Another commonly used process in image pre-processing is cropping, which involves removing undesired exterior regions from an image. This can be done to reduce incidental waste, improve the image's composition, alter the perspective or focus on a particular feature, or isolate the subject from its surroundings. Cropping can result in variations in the size of the images, as different portions of the image may be removed [27], [28].

To establish consistency among the input images, it is common practice to resize the cropped images to a standard size, known as resizing. This ensures that all images have the same dimensions, which is important for the subsequent stages of the object detection model, such as feature extraction and classification. It is worth noting that the specific image pre-processing techniques used may vary depending on the requirements of the object detection model and the characteristics of the images being analyzed. Researchers need to carefully select and justify the image pre-processing techniques used in their workflow to ensure that the processed images are suitable for accurate and reliable model training and inference.

- Image segmentation

Image segmentation is a fundamental image processing task that involves dividing an image into multiple regions or segments. This technique is widely used for object detection and boundary detection in various applications such as medical imaging, autonomous driving, and satellite imaging. In image segmentation, each pixel in the image is assigned a label or class to identify which object or region it belongs to. This process is known as segmentation, and it can provide much more detailed information about the image compared to other image processing tasks, as shown in Figure 4. Deep learning techniques have been successfully applied to identify, segment, and classify cracks in common images, such as asphalt, concrete, masonry, and steel surfaces [29].

There are generally two approaches used in the literature for crack detection: classification and segmentation. In the classification approach, small patches of an image are labeled as crack or non-crack. In the segmentation approach, each pixel in the image is labeled as crack or non-crack. Image segmentation plays a crucial role in crack analysis, as it is used to enhance the image containing the crack to make the crack more distinguishable. Image pre-processing algorithms for crack analysis can be categorized into global and local algorithms. Common global algorithms include contrast stretching and histogram equalization, which adjust the pixel values of the entire image. Local algorithms, on the other hand, apply input-output modifications based on local characteristics and may include techniques such as adaptive histogram equalization, bit planes, morphology, and multiscale processing.

Image segmentation tasks can be categorized into three types: semantic, instance, and panoptic segmentation. Semantic segmentation involves categorizing pixels in an image into different classes without considering any contextual information. It simply assigns each pixel to a specific class. Instance segmentation, on the other hand, groups pixels into segments based on instances of objects, regardless of their class. This allows for separating overlapping or similar object regions based on their boundaries. Panoptic segmentation is the most informative approach as it combines both semantic and instance segmentation. It provides segment maps of all objects of a specific class present in the image. It is important to note that the choice of image segmentation algorithm depends on the specific requirements of the application and the characteristics of the images being analyzed. Different algorithms have their own advantages and limitations, which need to be carefully considered. Table 3 provides an overview of major image segmentation algorithms along with their advantages and limitations.

Figure 4. Crack image segmentation [30]

Table 3. Image segmentation techniques

Techniques	Details	Advantages	Limitations
Edge-based method [31]	Edge detection is the process of finding edges in an image, and it is a critical step in grasping image aspects. Edges are believed to contain substantial information and possess meaningful characteristics. It significantly reduces the image size to be analyzed and filters out unnecessary data, retaining, and focusing exclusively on the image's critical structural characteristics.	It is ideal for photographs with more contrast between objects.	Not recommended for images with a lot of noise.
Thresholding method [32]	It focuses on detecting peak values based on the image's histogram to discover related pixels.	It does not necessitate complicated pre-processing, and it is very easy to do.	Many important elements might be overlooked, and threshold errors are prevalent.
Traditional segmentation algorithms [33]	Objects are obtained by dividing an image into k number of homogeneous, mutually exclusive clusters.	Proven approaches, enhanced by fuzzy logic, and more suitable for real-time use.	It can be challenging to determine a cost function for minimization.
Region-based method [34]	The algorithm constructs segments in region-based segmentation by separating the image into discrete components with comparable properties. These components are simply a collection of pixels. Region-based image segmentation algorithms begin by locating specific seed points within the input image-these can be very small pixels or much larger chunks.	It works great for photos with a lot of noise and accepts user markers for quick evaluation.	Consuming both time and memory.
Watershed method [35]	Watershed is a ridge approach, also known as a region-based method, based on topological image boundary interpretation.	The obtained segments are more stable, and the detected borders are distinct.	The calculation of ridge gradients is difficult.
Neural networks [1]	Image recognition is the method of using neural networks to segment images. It processes and recognizes visual aspects such as objects, faces, and handwritten text. This is because convolutional neural networks are designed to identify and manage high-definition picture data.	Simple implementation, no need to follow any sophisticated techniques, ready-to-use Python libraries, and more useful applications.	It takes a long time and is costly to train the model for custom and corporate graphics.

2.4.3. Machine vision and machine learning based object detection models

Object detection is a widely used technique in computer vision that involves identifying objects in images or videos. It utilizes machine learning or deep learning algorithms to generate meaningful results. Just like humans can quickly recognize and identify objects in images, computers aim to replicate this intelligence through object detection. Object detection involves two main tasks: object localization, which determines the location of objects in an image, and object classification, which assigns objects into different categories. In recent years, the field of computer vision, particularly object detection, has undergone significant advancements. Figure 5 depicts the increasing trend of scholarly works utilizing machine vision and machine learning approaches in this domain over time.

Sliding window and super-pixel grouping methods, such as multiscale combinatorial grouping [36], constrained parametric min-cuts (CPMC) [37], selective search [38], edge boxes [39], and object in windows [40], are among the most commonly used techniques for object identification. The region based convolutional neural networks (R-CNN) [41] approach, based on region proposal, is used as an object detector to categorize regions into objects or backgrounds. Viola and Jones [42] introduced Haar features for object detection, while histogram of oriented gradients (HOG) features [43] combined with linear support vector machines (SVM) [38], sliding window classifiers, and deformable part models (DPM) [44] were used to build deformable graphical models. The OverFeat technique [45] utilized convolutional feature maps with fully connected layers for efficient detection and classification. Another approach, called spatial pyramid pooling (SPP)-based detection, combined features from specific regions on the convolutional feature map and introduced them to a fully connected layer for classification [46].

The use of machine learning and deep learning techniques has greatly improved the field of object detection, allowing for more accurate and efficient identification and categorization of objects in images and videos. These advancements have paved the way for various applications, such as autonomous vehicles, surveillance systems, and object recognition in multimedia content. Continued research in this area is expected to further enhance the capabilities of object detection and enable new applications in diverse domains.

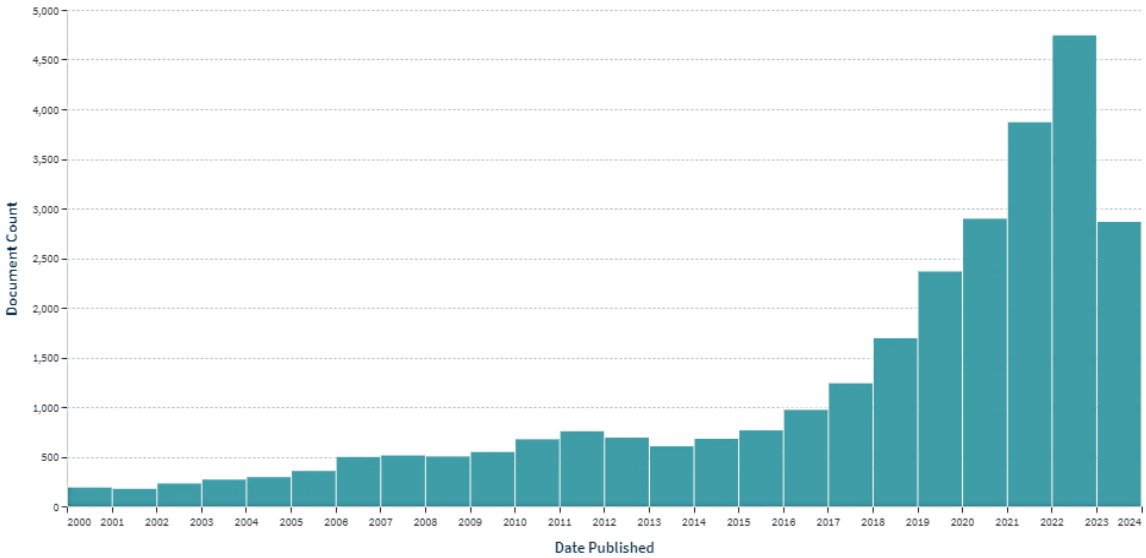


Figure 5. Scholarly works on object detection using machine learning from lens.org as of 2023

3. RESULTS AND DISCUSSION

3.1. Conventional techniques

Techniques used before the inclusion of machine learning and deep learning in pavement crack detection and classification are known as conventional techniques. Methods before including automation techniques were very laborious and time-consuming. Figure 6 shows the work of various researchers on road crack detection using conventional techniques. The detection of cracks was primarily conducted manually or using some sensor techniques. The main objective related to pavement cracks was focused on crack sealing and filling [47]. According to the general issue, the construction maintenance records were obtained for selection practice to determine the design, repairs to be done, and road age. Then a manual survey was conducted to detect cracks. The survey for crack detection would include the record of the amount of damage and severity of the pavement crack.

According to Jo and Ryu [48], the damage in pavement concrete designs can be actuated either by the dynamic or static burden. The four-point twisting test on the benchmark pavement concrete structure was utilized as a trial of the quality and affectability of the installed sensors. It permitted evaluation of whether any cracking and proliferation that happens with the implanted sensors can be recognized. Different strategies were utilized for the examination of the ultrasonic signs. The progressions in the construction were assessed by deciding the element from the ultrasonic signals. It is shown that the ultrasonic sensors can distinguish a crack with an accuracy of 100% before it is apparent by the unaided eye and different methods, regardless of whether the damage isn't in the immediate way of the ultrasonic wave. The acquired outcomes affirmed that early crack location is conceivable utilizing the created technique. Their work fosters an identification framework for the interior crack area and spread utilizing discrete strain sensors at the lower part of the substantial asphalts. Given straight versatile crack mechanics, a hypothetical methodology got from finding the base-up crack and following the crack spread utilizing at least two discrete in-asphalt strain sensors. Trial results showed that the proposed crack identification approach with two discrete strain sensors could distinguish base-up cracks with an average estimation precision of 82.4%.

Cracking in substantial asphalts is a significant worry for their exhibition, particularly the presence of the inner base-up cracks. These cracks might instigate water entrance in asphalt design and establishment so as to bringing about asphalt debasement. Early location of the cracks in substantial asphalts can speed up proper support, which works for the security of the framework. Numerous researchers have conducted crack detection investigations, each employing a unique technique. Using a dynamic thresholding method, Zhang *et al.,* [49] were able to identify dark pixels in pictures as likely being cracks. Their research uses entropy computation to divide threshold images into non-overlapping chunks. For this purpose, they generate an entropy block matrix and then utilize its dynamic threshold to locate blocks of the image that contain crack pixels. Zalama *et al.* [50] recommended a two-threshold distinction. A more sophisticated Otsu edge division algorithm was used to erase road markings from the runway picture. Then, the enhanced flexible, iterative limit segmentation algorithm was used to fragment the images that no longer included the markers. Finally, the crack's blueprint may be obtained by morphological denoising. Research by Akarsu *et al.* [51], they suggested a new multiscale ideal edge division algorithm for sectioning asphalt cracks using crack thickness appropriation. This technique accomplished a better division impact in contrast with the worldwide threshold technique.

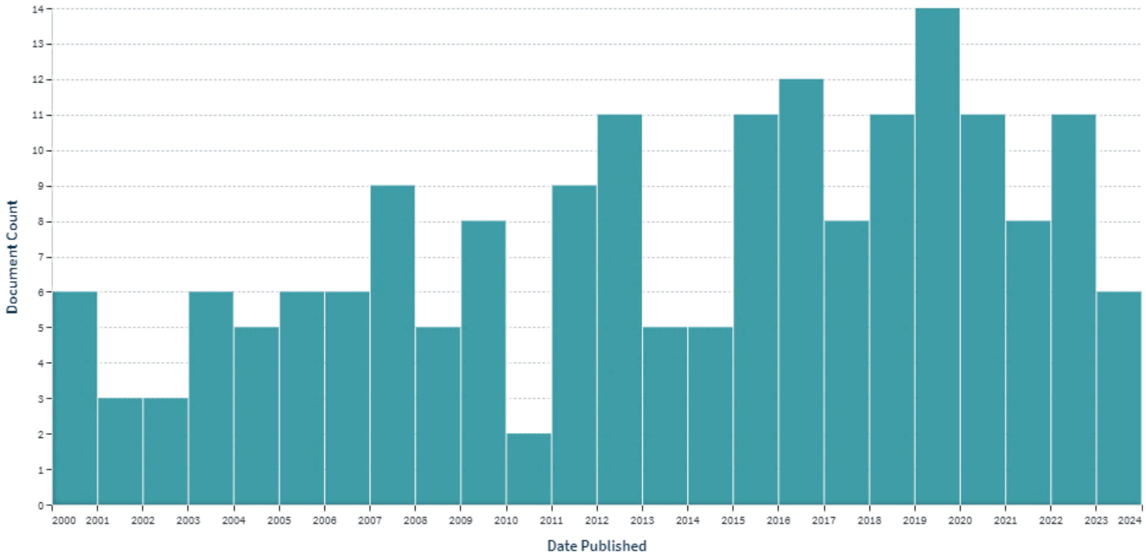


Figure 6. Conventional techniques-based scholarly works from lens.org as of 2023

Edge location strategies can likewise be utilized in crack detection. According to Amhaz *et al.* [52], they presented a new algorithm for detecting cracks in pavement images. The algorithm uses minimal path localization in each image, where a path's score is the sum of neighboring pixel intensities. The approach's originality lies in the method used to select minimal paths and the two post-processing steps introduced to improve detection quality. The approach considers both photometric and geometric pavement image characteristics and undergoes rigorous validation on synthetic and real images, producing robust and precise results in a fully unsupervised manner]. According to Li *et al.* [53], they concentrated on the crack location strategy, which joins bi-dimensional observational mode decay and Sobel edge location. Bi-dimensional observational mode decay [23] is an extension of observational mode decay that reduces noise from the signal without using sophisticated convolution measurements. The edge discovery calculation can obtain edge appropriation of crack deformities and blueprint crack shape, but this technique cannot solidly represent the data of the crack's interior pixels. The identification approach based on area development adds another layer of complexity to locating asphalt cracks. The primary idea behind region development is to amass comparable pixels in order to outline a region. Marques [54] examined the path and dealt with the asymmetric foundation component after pre-processing the road surface picture.

According to Cao *et al.* [55], occasional review and maintenance are fundamental for viable asphalt protection. In addition to affecting the road's appearance and diminishing the levelness, cracks also reduce the road's lifespan. In order to distinguish cracks in a practical manner, a crack detection method is created based on a grid network. This method utilizes a division network in addition to corner-based recognition. Corners are used to identify the crack region and a division network is built to make extracting the crack easier. The cracks' quantitative features were used to calculate limits, such as their length and breadth, with general errors of 4.23 and 6.98%, respectively, compared to the real values. Research by Fan *et al.* [56], they suggested a system for doing programmed asphalt crack examinations that use recorded crack information as a reference. From the start, a multiscale constraint approach was used to establish picture correspondences between recorded and probed crack images. This technique included global positioning systems (GPS)-based coarse constraint, image level constraint, and metric constraint. Then, verified crack pixels may be projected into the picture of the question crack and these projected crack pixels are recognized as excellent seed points for crack inquiry. Finally, the crack study is enhanced by including the locale developing strategy in order to differentiate newly generated cracks. The suggested technique was validated using real-world asphalt pictures accumulated over time. The F-measure for crack growth was determined to be 88.9%.

3.2. Machine vision and machine learning based techniques

The research works in pavement crack detection have been carried out with utmost enthusiasm. The advancements in recognition technologies and automation have highly boosted researchers to conduct their work in this sphere. Over the past decade, the rise in scholarly works in this field can be visualized in Figure 7.

Pavement surface review is principally founded on visual perceptions by people and quantitative examination utilizing costly machines. Among these, the visual review approach requires experienced road inspectors, yet additionally is tedious and expensive. Moreover, the visual examination will generally be conflicting and impractical, which expands the danger of developing road infrastructure. Considering these issues, regions lacking the necessary equipment do not direct road framework inspections as often. Interestingly, assurance dependent on enormous investigations, like utilizing a portable detection framework or laser-checking technique, is generally directed. GPS acquire exact geospatial data utilizing a moving vehicle, this framework involves a GPS unit, computerized quantifiable images, a computerized camera, a laser scanner, and an omnidirectional video recorder. However, quantitative inspection is accurate, but it is very costly to direct such far-reaching examinations, particularly for little districts that come up short on the necessary monetary assets. In this way, considering the previously mentioned issues, a few endeavours have been carried out to develop a strategy for examining pavement properties by utilizing a blend of techniques like in-vehicle cameras and image processing innovation to examine a road surface more effectively.

For instance, a past report proposed an automated black-top asphalt crack discovery technique utilizing image processing strategies and a Bayes-based AI approach [6]. Furthermore, a pothole-discovery framework utilizing a traffic camera has been recently proposed [57]. Lately, it has become conceivable to precisely examine the damage to road surfaces using deep neural networks. The review presented by Decker [58], focused on crack treatments in asphalt pavements, aiming to minimize water intrusion and prevent structural failures. By analyzing literature, surveying agencies and contractors, and developing best practices guidelines, the study provides up-to-date techniques for crack sealing and filling. For example, Zhang *et al.* [49] presented CrackNet, which predicts class scores for all pixels. Be that as it may, such pavement crack recognition strategies centre just around the assurance of the presence of a crack. A few examinations do group the crack dependent on types—for instance, [59] grouped crack types upward and evenly, [60] arranged cracks into three kinds, to be specific, upward, flat, and crocodile—most examinations principally centre around ordering cracks between a couple of types. In this way, it is important to recognize and distinguish different kinds of road cracks for a real-life crack recognition model.

An unsupervised road crack recognition method was put forth by Peng *et al*. [61] based on the dark histogram and Otsu strategy. According to Wang and Tang [62], excellent results were obtained when the signal-to-noise ratio was low. Using crack width measurements, researchers demonstrated an improved unsupervised learning algorithm based on least squares that lowered the circle and peak errors in crack detection. According to Zhao *et al.* [63], they used an approach based on the window's base power to isolate emerging fractures at each scale in the picture, analyzed the comparative relationships between various scale cracks, and constructed a crack evaluation model using multivariate statistical theory. To address the challenges of lopsided edge fractures with complex topological structures, an arbitrary design forest-based pavement crack identification system was proposed in [64]. To develop the irregular forest model, the fracture characteristics from different levels and orientations were retrieved.

According to Prah and Okine [65], they proposed a programming methodology for recognizing asphalt cracks. Pre-processing of the crack image begins by smoothing its surface and improving any existing cracks. For each non-overlapping square, a support vector is generated using the supervised learning technique SVM, which is subsequently utilized to distinguish cracks. As a result, careful calculation planning is required when employing these techniques. Recently, deep learning techniques have made significant progress in various machine vision applications, including picture classification, object identification, and image segmentation [66]. Numerous algorithms based on deep learning, most notably deep convolutional neural networks (CNN), have been developed for road crack identification. These approaches may typically be classified into three categories based on how they approach the crack identification problem: pure picture grouping strategies, object location-based strategies, and pixel-level strategies. They used a single CNN model in [67] to develop expertise with the building of asphalt cracks as a multi-name categorization problem. According to Li *et al*. [68], they introduced DeepCrack, a method for segmenting asphalt picture pixels into cracks and foundations using an encoder-decoder architecture. Research by Wang *et al.* [69] developed a network topology that used four convolutional layers and maximum pooling as an encoder to eliminate components, then four subsequent modules as a decoder.

The various AI-based crack detection models are presented in the chart shown in Figure 8. The crack detection models have been classified as machine learning and deep learning based. When it came to detecting pavement cracks using machine learning in the earlier phase, supervised learning models were more commonly used than unsupervised learning models, which was a significant improvement over unsupervised learning models. However, a significant shift has been seen after introducing deep learning object detection models to yield better results. Deep learning algorithms are combined with other machine learning approaches, resulting in a hybrid model.

Because of the significant number of research conducted on pavement crack detection and classification, along with a significant number of articles that have been published, it is necessary to organize, summarize, and analyze this vast quantity of work. Table 4 summarises some more studies on pavement crack identification and classification. Critical insight into various literature related to this field can be examined, along with their strengths and limitations.

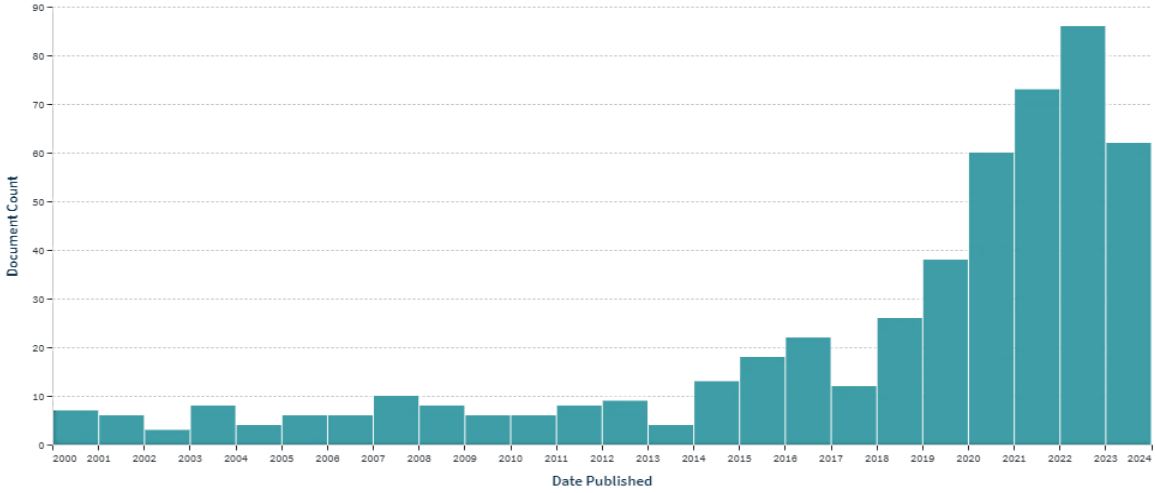


Figure 7. Machine vision and machine learning based scholarly works from lens.org as of 2023

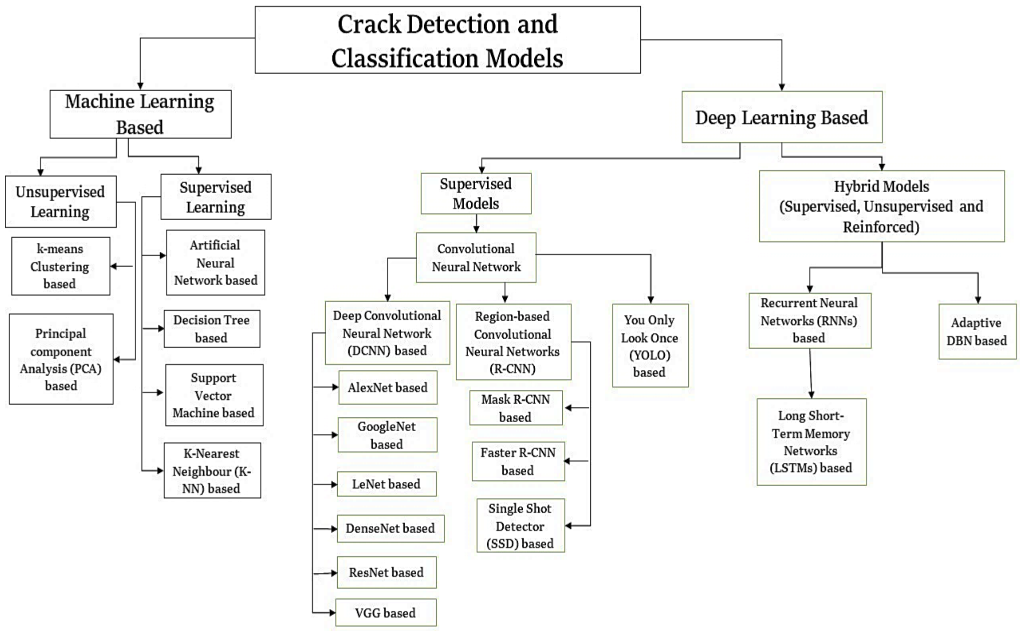


Figure 8. Classification of crack detection models based on AI techniques

Table 4. Recent related works

Research title	Method used	Strength	Limitations
Automatic pavement crack detection based on structured prediction with the CNN [56]	CNN	Generalizing data and using hybrid data for training the model performance was promising. Cross-testing further boosted the labelling process. The system attained an accuracy of 90%.	The positioning of the crack pixels has not been taken into consideration. It only focuses on either crack present or not present.
Pavement crack detection and segmentation method based on improved deep learning fusion model [1]	Deep CNN fusion, U-Net model.	In this model, optimization of crack classification hyperparameters was implemented. They formulated their dataset and evaluated the same on the proposed model. In this system, crack length was calculated utilizing pixel labelling and scanning.	The average accuracy of the model was not promising at about 78.7%.
Road damage detection using deep neural networks with images captured through a smartphone [70]	Deep neural networks	The proposed system was trained and tested on the self-created dataset. Working in collaboration with Japan's local governments, 163,664 images were acquired.	The length of the cracks was not taken into consideration. Also, the recall and precision of the dataset were not of superior quality, i.e., 75%.
Feature pyramid and hierarchical boosting network for pavement crack detection [71]	Deep supervision learning	This technique used feature pyramid and hierarchical boosting techniques to enhance the low-level features. The model's crack recognition time is significantly less.	The experimental results are majorly evaluated on time. Accuracy, recall, and precision-like results are lacking.
Road crack detection using deep CNN [72]	Supervised deep CNN	CNNs were implied for this research which performed better than other traditional techniques like boosting and SVM. The performance parameters in terms of recall reached a percentage of 92.51.	The system uses manual annotation for images. Also, the feasibility of this research is not promising in terms of cost and real-life scenarios. The crack length has not been taken care of.
Automatic detection of cracks in asphalt pavement using deep learning to overcome weaknesses in images and GIS visualization [73]	CNN	The proposed model has been incorporated with ResNet and the geographic information system. Moreover, a mobile mapping system has been implemented for this work. The system attained an accuracy of 94.3%.	There are some FPs in the model showing cracks in non-crack images. Refining of crack image pixels was not highly promising.
Image enhancement algorithm on ridgelet domain in detection of road cracks [74]	Wavelet decomposition, ridgelet transform, image enhancement	A new image upgrade calculation in ridgelet space was proposed to identify road cracks. Experiment results and their correlations with other image improvement calculations show that the analysis can be utilised to upgrade road crack images and is practical in recognizing road cracks.	A more traditional technique is not feasible in the present scenario.
Automatic crack detection of road pavement based on aerial UAV imagery [75]	SVM, edge-based approach	This work proposes a programmed technique for crack recognition out and about asphalt using procured recordings from the UAV stage. Choosing key edges and creating Ortho-image, violating non-road areas in the scene are taken out. Then, at that point, through an edge-based methodology theory, crack components are extricated.	The accuracy of the proposed model is not promising and came out to be 75%.
Road crack detection using CNN [76]	CNN, SVM	The proposed model can recognize crack and non-crack images and is ready to order the longitudinal crack from other given crack images. The proposed road crack recognition procedure gives high precision of about 98% contrasted with before standard strategies.	Despite good accuracy, the model is more simple detection oriented than the classification of cracks, which provides more information regarding road damage.
Pavement crack detection based on YOLO v3 [77]	Deep learning, YOLO v3	YOLO v3 network training has been incorporated. The cracks are detected and verified using the same model. The accuracy of the system came out to be 88%.	Labelling is manually done. The crack classification has not been emphasized.

3.3. Crack characterization

Crack characterization, which involves identifying the type and size of detected cracks, is crucial for road maintenance in addition to crack detection and classification. In earlier times, a manual approach was followed by road and maintenance personnel, which was time-consuming and resource-intensive. However, a computerized framework for crack characterization based on the Portuguese trouble catalog was proposed [78]. This framework utilized a combination of two Gaussian models for unsupervised crack detection, serving as a guide for conducting asphalt crack examinations [69]. The method was tested on asphalt photos taken at various times and involved a multiscale limiting method with GPS-based coarse restriction, image level confinement, and metric confinement to compare inquisitive crack pictures. The original crack pixels were then plotted onto the inquiry crack picture as ideal seed points for crack investigation and the region growing method (RGM) was used to improve crack detection and identify new cracks that had formed recently. The proposed approach was found to improve crack research results by 88.9% based on the F-measure.

Research by Oliveira and Correia [60], developed a novel framework for automated crack identification and categorization based on survey images taken at high driving speeds. The survey images were pre-processed with morphological filters to reduce pixel intensity variation. A dynamic thresholding method was then applied to identify dark pixels in the image that corresponded to likely crack pixels. Entropy-based thresholding was used to further analyze the image and the resulting entropy blocks matrix was used to identify picture blocks that contained crack pixels. The image was then classified into horizontal, vertical, miscellaneous, or no cracks based on the classification system. Two picture databases were used for testing, including one taken with professional high-speed equipment, to establish the robustness of the approach. The use of machine learning techniques in crack characterization has significantly improved the process, allowing for block-level and pixel-level segmentation for type identification and size estimation of detected cracks. Overall, these automated frameworks for crack characterization based on computer vision and image processing techniques have shown promising results in terms of improving the efficiency and accuracy of crack analysis, reducing the manual effort required, and enhancing the robustness of crack detection and classification in road maintenance applications.

3.4. Comparison of various crack detection and classification models based on performance parameters

Various studies have identified the presence of cracks and type prediction as primary evaluation criteria for detecting and categorizing pavement cracks. To assess the performance of crack detection and classification models, metrics such as accuracy, precision, sensitivity, and F1 score are commonly used and calculated using (1)-(4) respectively.

- Accuracy: accuracy measures the overall correctness of the model's predictions by calculating the ratio of correctly predicted instances to the total number of instances. It provides a general measure of how well the model is performing in terms of correctly identifying cracks and predicting their types.

$$Accuracy\ Score = (TP + TN)/(TP + FN + TN + FP) \tag{1}$$

- Precision: precision measures the proportion of true positive predictions out of the total positive predictions made by the model. It indicates the accuracy of the positive predictions made by the model and is particularly relevant when the cost of false positives is high, such as in safety-critical applications.

$$Precision\ Score = TP/(FP + TP) \tag{2}$$

- Sensitivity (also known as recall or true positive rate): sensitivity measures the proportion of true positive predictions out of the total actual positive instances. It reflects the model's ability to correctly detect cracks among all the actual cracks present. Sensitivity is important when the cost of false negatives (missed cracks) is high and is used to assess the model's ability to minimize false negatives.

$$Recall\ Score = TP/(FN + TP) \tag{3}$$

- F1 score: the F1 score is the harmonic mean of precision and recall. It provides a balanced measure of both precision and recall. This is particularly useful when both false positives and false negatives need to be minimized. A high F1 score indicates a good balance between precision and recall, a higher value is generally desired.

$$2 \times Precision\ Score \times Recall\ Score/(Precision\ Score + Recall\ Score) \tag{4}$$

However, these evaluation criteria are often impacted by the skewness in the datasets used to build the model, leading to dramatic effects on their performance. When creating a crack detection and classification model, several factors must be considered, including data collection and pre-processing techniques, hyperparameter tuning, and generalizability of the model. The confusion matrix is a useful tool for calculating evaluation parameters such as accuracy and precision. Figure 9 provides a visual illustration of how “true positive, true negative, false positive, and false negative” can be computed to determine recall, precision, accuracy, and specificity [17].

In recent research, the use of neural networks and deep learning algorithms for crack identification and classification from images and videos has gained significant attention. CNN, modular neural network [79], residual depthwise separable CNN [80] and recurrent neural network are examples of neural networks used in this field. Other methods such as YOLO, SSD, ResNet, UNet, and LeNet have also been employed. Table 5 provides a comparison of the performance parameters of a few researchers in this field.

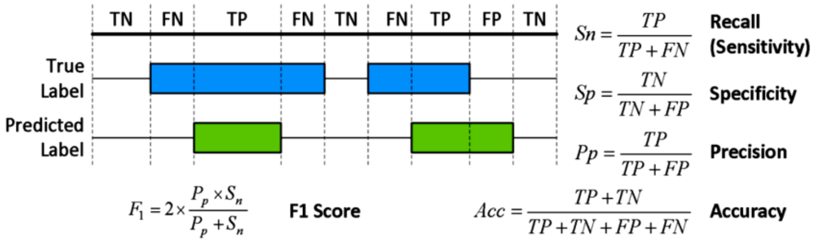


Figure 9. Performance metrics in machine learning

Table 5. Machine learning-based model performances

Method	Results	Citation
SVM	Precision=0.81, 0.73, 0.86	[72]
Boosting	Recall=0.67, 0.75, 0.92	
Conv nets	F1 score=0.73, 0.74, 0.89	
Convolutional neural network	Precision=0.911 Recall=0.948 F1 score=0.922	[56]
GoogleNet CNN, FPN	Precision=0.80 Recall=0.86 F1 score=0.81	[81]
Random structured forests, SVM	Precision=0.96	[82]
CNN	Precision=0.8696 Recall=0.9251 F-measure=0.8965	[83]
Deep convolutional encoder-decoder network	Recall=0.71 Precision=0.77 The intersection of Union=0.59	[84]
CNN	Precision=0.90 Recall=0.87 F-measure=0.88	[85]

CNN-based deep learning models consistently demonstrate strong performance across different implementations, with most achieving precision, recall, and F1 scores above 0.8. The inherent architecture of CNNs, which excels at processing grid-like data such as images, may account for their superior performance. By utilizing local connectivity, weight sharing, and pooling operations, CNNs are able to automatically learn, capture hierarchical patterns, and spatial features from the input data, thereby enhancing their ability to generalize and make accurate predictions. These findings underscore the overall effectiveness of CNN-based models in the machine learning based crack inspection, while also highlighting performance variations depending on specific implementations.

3.5. Challenges

Over the past decade, pavement crack detection and classification have emerged as significant areas of research in both human-computer interaction (HCI) and image processing domains. The extensive research in this field reflects the high demand for this technology, which combines knowledge from civil infrastructure and human-computer interface disciplines in practice. One of the primary challenges in developing pavement crack detection and classification models is data acquisition. Data plays a crucial role in machine learning model development and any issues with the data will adversely impact the model's performance. Researchers often use online datasets for their work, which may not generalize well to real-world data. To improve model performance, it is essential to focus on collecting and utilizing data that closely represents real-world scenarios. The datasets used for model training may not have a balanced distribution of crack types and severities, which can lead to biased models with poor performance on underrepresented crack classes. Addressing this issue requires careful dataset curation and the application of techniques such as data augmentation and balanced sampling.

Another challenge stems from noise in the input image or video data, including shadows, pixel intensity changes, Gaussian noise, and salt-and-pepper noise. Such noise negatively affects the performance of the developed model. While researchers employ various pre-processing techniques to address these issues, there is still a need for more refined digital image processing methods to enhance the quality of input data.

Pavement surfaces can vary in terms of materials, texture, and crack patterns. A model that performs well on one pavement type may not generalize effectively to others, necessitating the development of more versatile and adaptable models. In practical applications, crack detection and classification systems may need to process data in real time. This requirement imposes constraints on the computational complexity of the models, necessitating the development of efficient algorithms that can deliver accurate results without causing significant delays.

Reducing dimensionality and selecting features represent additional challenges in the development process. Feature selection is often computationally expensive and unfeasible due to the complexity of identifying the most suitable feature subset from a vast set of features. CNNs have proven effective in addressing this issue, as they generate new features from original ones to reduce the total number of features in a dataset. These derived features should be capable of effectively summarizing the original feature set.

The success of a crack detection and classification system heavily depends on the classifier's ability to interpret the algorithm's output. Traditional machine learning algorithms pose various challenges as classifiers. For instance, the training process for a classic CNN is extensive due to max pooling, and the processing time for traditional classifiers like KNN, decision tree, and SVM increases with the size of the dataset. To overcome these challenges, researchers can explore various deep learning algorithms and architectures, such as ResNets, U-Nets, YOLO, DenseNets, and SSDs. Numerous issues and challenges arise at different stages of developing pavement crack detection, classification, and characterization model. To minimize error rates and improve evaluation results, researchers must carefully navigate each step from data acquisition and annotation to model development and evaluation.

4. CONCLUSION

The automated recognition of pavement cracks has been inspected broadly because of its viable significance. From conventional image processing strategies to AI techniques to deep learning methods, it has become a trending research topic in recent times. This review paper aims to provide a comprehensive literature study about state-of-the-art techniques proposed and utilized by researchers in detecting, classifying, and characterizing pavement cracks. This paper describes various types of cracks associated with concrete and bituminous pavements. Various related works have been reviewed, and their methodologies and outcomes have been briefly described. The generalized crack detection, classification, and characterization architectural framework using image processing and machine learning techniques has been presented in this review. Also, various data acquisition techniques and image classes are presented. Since finding appropriate data for model development is highly important, this paper presents a list of various available datasets along with their descriptions. This paper also compares different crack detection and classification models based on performance parameters and highlights a few open challenges that researchers in this area face.

The automated recognition of pavement cracks has been extensively studied due to its practical significance. From conventional image processing techniques to AI and deep learning methods, it has become a prominent research topic in recent times. This review paper aims to provide a comprehensive literature study on the state-of-the-art techniques proposed and utilized by researchers for detecting, classifying, and characterizing pavement cracks.

This paper provides a detailed overview of various types of cracks associated with concrete and bituminous pavements, and reviews related works along with their methodologies and outcomes. The paper also presents a generalized crack detection, classification, and characterization architectural framework using image processing and machine learning techniques. Additionally, different data acquisition techniques and image classes are discussed in this review. Since obtaining appropriate data for model development is crucial, this paper also presents a list of various available datasets along with their descriptions. Furthermore, the paper compares different crack detection and classification models based on performance parameters and highlights some open challenges that researchers in this field face.

To summit up, this review paper provides a comprehensive overview of the current state-of-the-art techniques for pavement crack detection, classification, and characterization. It highlights the importance of data acquisition, presents a generalized architectural framework, and discusses various challenges in this area. This review serves as a valuable resource for researchers and practitioners interested in pavement crack detection and analysis.

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