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*Review*

# How to Make a State of the Art Report—Case Study—Image-Based Road Crack Detection: A Scientometric Literature Review

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**Abstract:** With the rapid growth in urban construction in Malaysia, road breakage has challenged traditional manual inspection methods. In order to quickly and accurately detect the extent of road breakage, it is crucial to apply automated road crack detection techniques. Researchers have long studied image-based road crack detection techniques, especially the deep learning methods that have emerged in recent years, leading to breakthrough developments in the field. However, many issues remain in road crack detection methods using deep learning techniques. The field lacks state-of-the-art systematic reviews that can scientifically and effectively analyze existing works, document research trends, summarize outstanding research results, and identify remaining shortcomings. To conduct a systematic review of the relevant literature, a bibliometric analysis and a critical analysis of the papers published in the field were performed. VOSviewer and CiteSpace text mining tools were used to analyze and visualize the bibliometric analysis of some parameters derived from the articles. The history and current status of research in the field by authors from all over the world are elucidated and future trends are analyzed.

**Keywords:** road crack detection; deep learning; scientometric analysis



**Citation:** Fan, L.; Tang, S.; Mohd Ariffin, M.K.A.b.; Ismail, M.I.S.b.; Zhao, R. How to Make a State of the Art Report—Case Study—Image-Based Road Crack Detection: A Scientometric Literature Review. *Appl. Sci.* **2024**, *14*, 4817. https://doi.org/10.3390/app14114817

Academic Editor: Sungho Kim

Received: 9 May 2024
Revised: 29 May 2024
Accepted: 31 May 2024
Published: 2 June 2024



## 1. Introduction

With Malaysia's rapid economic development, the demand for roads and highways is growing significantly [1]. Currently, Malaysia has 267,045.58 km of roads, of which 198,437.92 km are paved. The extensive transportation network effectively improves connectivity between cities and lays the groundwork for the country's development. Over time, the deterioration in road conditions and the gradual emergence of various road problems have presented challenges to road management, inspection, and maintenance. Long-term use of roads has resulted in high maintenance and repair costs, leading to a significant allocation of financial resources to road maintenance, with an estimated annual budget for road maintenance in Malaysia exceeding MYR 4693 million [2]. With the growth of road life, the road surface gradually began to appear cracked, broken, and have other problems. An uneven road surface greatly improves the probability of traffic accidents, so timely road repair and maintenance are of great significance.

Traditional road inspection methods not only require a large amount of labor and consume a lot of time but also require the closure of roads [3]. These practices cause localized road blockages and reduce vehicle traffic efficiency, but they also increase the probability of traffic accidents and pose safety risks. To address these challenges, computer vision and machine learning have revolutionized road crack detection techniques. Combining high-resolution cameras with neural networks to detect road cracks by robots effectively unifies detection standards, resulting in a significant improvement in the accuracy and efficiency of detection [4]. This technological shift marks a new era in pavement management, moving away from traditional labor-intensive methods to more efficient, accurate, and cost-effective solutions [5]. The combination of machine learning and computer vision in pavement management is extremely important to address the challenges posed by the rapid expansion and aging of road infrastructure. These technological advances are becoming increasingly important as the demand for transportation infrastructure continues to grow. They not only play a crucial role in maintaining the infrastructure and improving the durability and reliability of roads but also reduce the rate of traffic accidents brought about by the inspection process. In the long run, these technologies make an outstanding contribution to smarter and more sustainable management of infrastructure, in line with the global trend towards automation and data-driven decision-making in urban planning and development [6].

Crack detection is divided into three steps: first crack image acquisition, then preprocessing of the acquired image, and finally classification, detection, and segmentation of the processed image. Researchers have applied various types of images to the field of cracks, such as RGB (red, green, and blue) images [7], infrared ray images [8], ground-penetrating radar images [9], etc. Image preprocessing methods include grayscale conversion [10], binary conversion [11], k-means clustering [12], fractal dimension, thresholding [13], edge detection [7], etc. Image processing techniques can be effective in extracting features and reducing the negative impact on the environment. Different methods classify, detect, and segment the cracks after extracting the features. In order to enhance crack detection, contemporary researchers are increasingly favoring deep learning-based image recognition algorithms such as convolutional neural network (CNNs) [14], You Only Look Once (YOLO) [9], and U-Net [15], etc. This is due to neural networks' ability to autonomously extract essential features from road crack images in order to detect cracks more accurately.

With advancements in image processing algorithms, vision-based crack detection systems are becoming increasingly popular. This particular field has been the focus of a certain number of scholarly articles. However, there is a distinct lack of relevant systematic review papers in the field that provide bibliometric analysis and critical analysis of the existing literature. This paper aims to demonstrate research trends and provide a succinct overview of the field of road defect detection. The authors conducted a systematic review by examining notable papers focusing on image-based crack detection algorithms published between 2013 and 2023. This review aims to fill the gaps in the existing literature and provide valuable information to new researchers in this research area. This work focuses on research papers from 2013 to 2023 as a basis for research in this field. This study aims to examine the evolution of this field and the current state of research.

This review paper's main contributions are as follows.

(a) The authors conducted a bibliometric analysis of selected papers in the image-based road detection research direction, using data mining techniques to identify research trends, influential papers, journals, authors, and countries in the field, as well as explore patterns of collaboration in this research area.
(b) The authors conducted a critical analysis of papers related to deep learning-based methods for road crack image detection.
(c) The authors summarize important image processing techniques and classifier algorithms for road crack detection.

## 2. Literature Review

As science and technology have advanced, computer vision—a technology based on image processing—has become an increasingly important field of study for road crack detection. This technique has made an excellent contribution to the automation of the crack detection process. This approach has now become a key research area for researchers and engineers. This section provides a brief overview of key elements from previous review papers and explores the significance of contemporary works that have contributed significantly to the research area.

Refs. [7,13] discussed the use of image processing for road crack detection, focusing on basic techniques such as thresholding, edge detection and region growing methods. There are some problems with manual inspection that require automated systems [7]. multiscale extraction and Markovian segmentation methods were introduced. Ref. [13] gave an in-depth look at how computer vision can be used to assess the condition of civil infrastructure. Ref. [16] presented a study showing how the advancement of mobile light detection and ranging (LiDAR) technology has led to a shift in focus towards the collection of three-dimensional (3D) point clouds for road information inventory. In [17], image processing and machine learning methods for road damage detection were further explored, emphasizing the importance of automated and semi-automated evaluation systems. Ref. [18] highlights the achievements and challenges of applying deep learning in this area, indicating a rapidly growing interest in such approaches due to their superior performance over traditional methods. This period marked a significant shift in deep learning methods, in particular deep convolutional neural networks (DCNNs) for automated road breakage detection. In [19,20], the refinement of deep learning and the introduction of 3D imaging were explored, deep learning methods were categorized into classification, detection and segmentation, and 3D image-based crack detection techniques were introduced. These papers discuss the performance comparison of different deep learning models and the potential of 3D data to improve detection accuracy. Recent advances in sensing technologies, machine learning methods and image processing for road monitoring and analysis are discussed in [21,22]. In [21], the focus is on image segmentation and the need for advanced segmentation strategies to enable fully automated pavement distress detection. Ref. [22] emphasizes the need to improve the performance of intrusive sensors and algorithms to better adapt to different road images. Table 1 summarizes the review paper on crack detection using image processing techniques.

**Table 1.** Summary of previous review of crack detection using image processing techniques.

| Ref | Year | Name of the Journal/Conference | Major Contributions | Limitations |
|---|---|---|---|---|
| [7] | 2011 | International Journal of Geophysics | Introduced multi-scale extraction and Markovian segmentation for crack detection in pavements. Offered a new method and evaluation protocol for crack detection. | Method's dependency on the quality of road texture and limitations of the acquisition system highlighted. |
| [13] | 2015 | Advanced Engineering Informatics | Comprehensive review of computer vision applications for infrastructure condition assessment. Synthesized state of the art in defect detection. | Existing methods' achievements and limitations outlined without providing a definitive solution to address the challenges. |
| [16] | 2016 | International Journal of Image and Data Fusion | Discussed the advancements in mobile LiDAR technologies for road information inventory. | Highlighted the need for further exploration in mobile LiDAR technologies and data processing techniques. |
| [17] | 2017 | Archives of Computational Methods in Engineering | Comprehensive review of image processing and machine learning approaches for pavement distress detection. | Costly industrialization and the need for more powerful tools for better image quality emphasized. |
| [18] | 2018 | Data | Reviewed applications of deep learning in automated pavement distress detection, comparing deep learning frameworks and architectures. | Identified class imbalance in pavement images as an area needing further research within deep learning contexts. |
| [20] | 2020 | IEEE Access | Reviewed image processing, machine learning, and 3D imaging methods for crack detection. Compared deep learning neural networks. | Acknowledged the emergence of 3D data in crack detection as a new research line but detailed exploration required. |
| [19] | 2020 | Journal Of Computing In Civil Engineering | Reviewed and evaluated ML-based crack detection algorithms, focusing on pixel-level segmentation. | Pointed out the false-positive problem as a key issue needing improvement in ML-based crack detection models. |

**Table 1.** *Cont.*

| Ref | Year | Name of the Journal/Conference | Major Contributions | Limitations |
|---|---|---|---|---|
| [22] | 2021 | Engineering | Summarized state-of-the-art in sensing techniques, image processing, and ML methods for pavement monitoring. | Suggested improvement in sensors and algorithms for better adaptability and performance. |
| [21] | 2022 | Construction And Building Materials | Focused on image segmentation approaches in crack detection, reviewing thresholding-based, edge-based, and data-driven methods. | Highlighted the need for advancements in algorithms to handle diverse pavement conditions and complex textures. |

Throughout this evolution, a clear shift from manual and semi-automated techniques to sophisticated deep learning and 3D imaging methods has occurred, reflecting broader trends in technology and data science. Together, these papers emphasize the importance of continued innovation in algorithms, data processing techniques, and sensor technologies to effectively address the challenges of road crack detection. Future research directions focus on enhancing deep learning models, exploiting the potential of 3D imaging, and developing comprehensive systems that integrate various data types and detection methods to assess road conditions more accurately and effectively.

## 3. Research Methodology

The authors used a combination of methods in this work, including a bibliometric analysis and a critical analysis of papers. The main focus of the study is on the algorithms used for road crack detection. Figure 1 illustrates the overall technique used in this research.

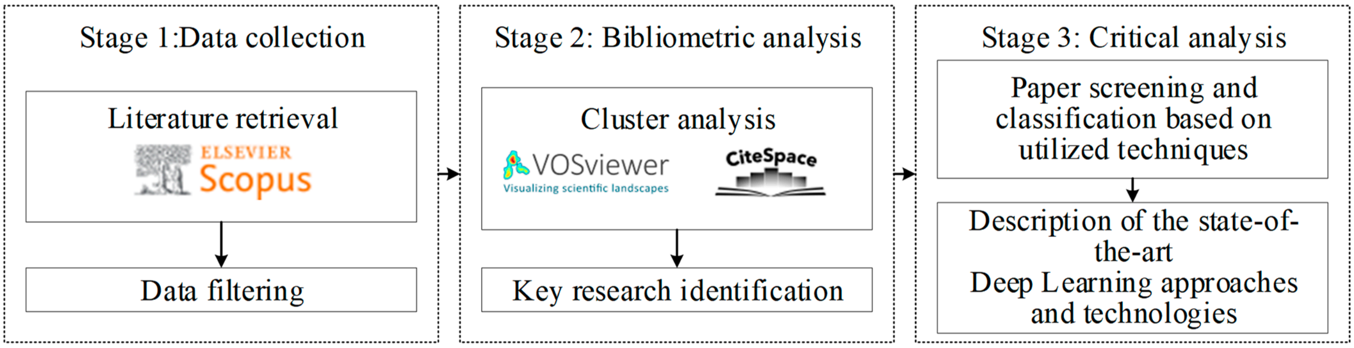


**Figure 1.** Overview of the research methodology.

As shown in Figure 1, the first stage is the collection of the original paper data for this review. The second stage is a bibliometric analysis to identify key areas of research. The third stage involves a careful evaluation of the papers, focusing on the abstract, methodology, and results. In addition, a brief summary of the progress made in the development of algorithms for road crack detection is provided.

In order to conduct a comprehensive literature review, the authors followed a predetermined set of criteria to include the most relevant scientific papers. Figure 2 shows the process of document retrieval and data filtering, referred to as stage 1 in Figure 1. According to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach, there are four separate steps in the data collection process: identification, screening, eligibility, and inclusion [23].

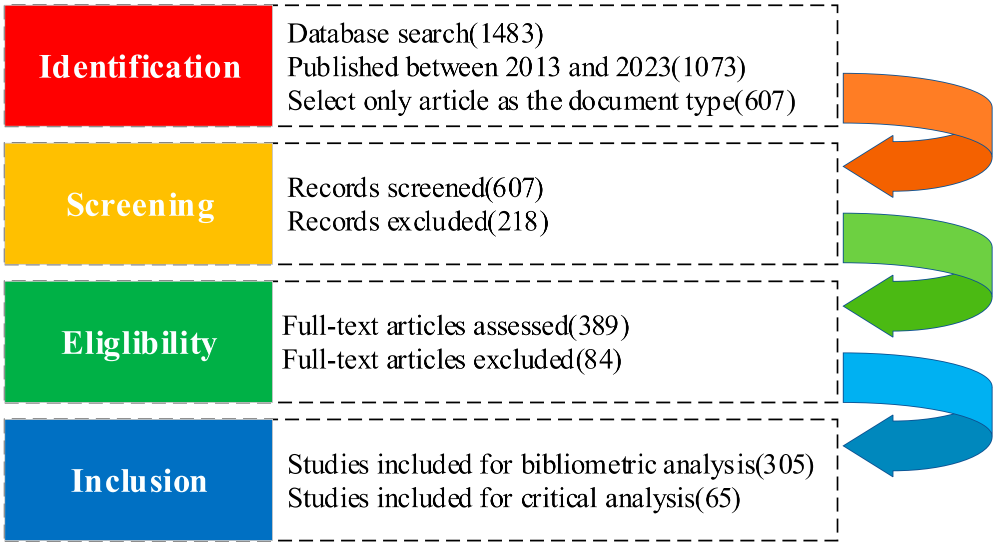


**Figure 2.** Overview of the literature retrieval and screening process.

Phase 1: In March 2024, the authors searched for papers on Scopus. To discuss the development of crack detection and the latest technologies, the author restricted the search string to a period from 2013 to 2023, using the search keywords "pavement crack detection". Only articles were selected as the document type to ensure that it was an original study. At the end of the first phase, the authors identified a total of 607 papers.

Phase 2: The authors filtered eligible papers from the 607 extracted papers by title and abstract. In order to avoid the inclusion of irrelevant papers, the authors established rules to exclude and discard these papers if (a) the focus of a particular paper was a non-image-based crack detection algorithm, (b) the paper dealt with the detection of non-road cracks (such as walls, steel, etc.), (c) the paper investigated the method of detecting non-surface road cracks. The application of these rules resulted in the exclusion of 218 papers at this stage.

Phase 3: At this stage, the remaining 389 papers were evaluated using the full text of the survey. Papers that were not related to the research topic of this study or that did not make an innovative and effective contribution to the field of image-based crack detection research were eliminated. In sum, 84 papers were excluded. This reduced the number of papers extracted to 305.

Phase 4: Upon completion of all the above phases, 305 papers were finally included in this review for scientific measurement analysis (at https://drive.google.com/file/d/1WbbGcwvawm8o-3rjK1uiJMp1qaE5oJ6L/view?usp=drive_link (accessed on 3 May 2024), and 72 papers based on deep learning were selected from the 305 papers. After excluding papers that did not provide detailed processes for designing or implementing the proposed ideas, 65 papers were finally selected for critical analysis.

## 4. Bibliometric Analysis

Bibliometric analysis is a statistical approach used to evaluate the academic merit of papers, publishers, and authors. It also helps identify research trends in a given field by analyzing factors such as the number of publications, their citation frequency, and patterns of collaboration. The authors used two visualization tools, namely, VOSviewer [24] and CiteSpace [25], to perform a bibliometric analysis of papers obtained from a screened database. The authors explored the most influential papers, authors, publishers, and countries in the research area of image-based crack detection algorithms for roads. In addition, the authors performed a scientific mapping analysis. The scientific mapping analysis includes co-citation analysis, co-authorship analysis, keyword occurrences, and timeline view analysis. Co-citation analysis determines the relevance of different papers. Co-authorship analysis can identify patterns of collaboration between countries and institutions. The number of keyword occurrences gives an idea of research trends and important terms in the field.

## 4.1. Overview of the Publications

### 4.1.1. Annual Analysis of the Publications

The authors screened papers from the online database Scopus between 2013 and 2023, analyzing a total of 305 papers for bibliometric analysis. Figure 3 shows the number of papers per year. The figure shows a low publication rate from 2013 to 2015, with fewer than five papers published per year. After 2016, the number of papers published per year began to increase rapidly, fluctuating between 10 and 20 between 2016 and 2019. In 2020–2021, the number of papers published increased dramatically, jumping to between 40 and 50, while in 2022–2023, the number of papers was between 70 and 80, accounting for about 58.52% of the total number of papers published at that time. In 2024, the publication rate also showed an upward trend. This clearly shows that researchers are beginning to invest more effort in this field of study, and the analysis predicts a significant increase in the number of papers in this field to continue.

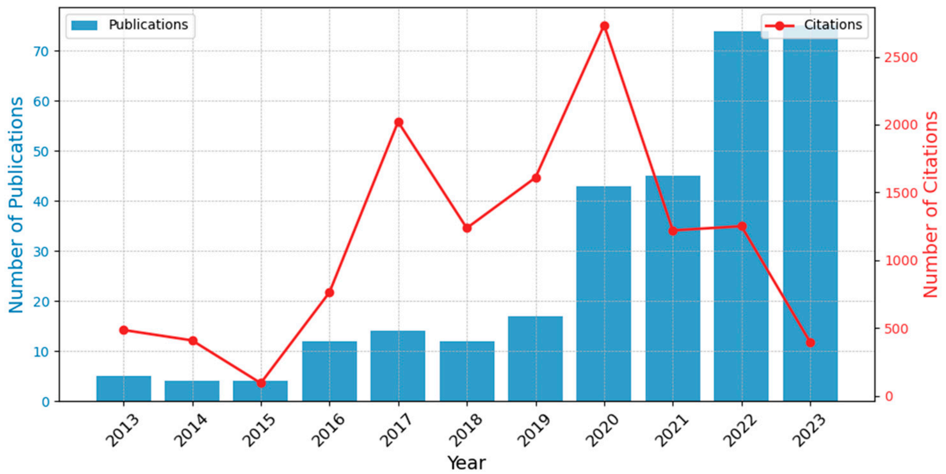


**Figure 3.** Summary of annual characteristics of the papers.

The authors also analyzed the number of citations to the papers by year. Figure 3 shows the distribution of citations per year for papers. The figure shows a consistent upward trend in citations over time. The figure shows that the authors have divided the time span from 2013 to 2023 into three stages, with the first stage (2013 to 2016) showing fewer than 80 citations per year, for a total of 1752 citations. This is only 14.34% of the total number of citations. In the next stage (2017–2020), the number of citations showed a rapid increase. The highest number of citations in this stage is 2734 in 2020, followed by 2021 in 2017. In this stage, the total number of citations is 7601, which represents 62.20% of the total number of citations. In the last stage (2021–2023), there is a decrease in the number of paper citations, with a total of 2868 citations. This stage accounted for approximately 23.47% of the total citations. This suggests that the field has experienced significant growth in recent years, with the literature from 2017 to 2020 making a significant contribution to the field. The authors argue that the lower number of citations to papers from 2021 to the present does not mean that this stage of research has stagnated, as the number of citations in the literature in this stage is still significantly higher than in the first stage and is similar to the average number of citations per year in the second stage. The literature of the last stage, which was published later and over a shorter period of time (only two or three years), resulted in a relatively low number of citations.

4.1.2. The Most Cited Publications

In this subsection, the authors identify and analyze the most influential and popular papers out of the 305 papers. The authors set a threshold of at least 100 citations to extract 25 papers. The authors cited these 25 papers 5732 times, accounting for about 46.90% of all paper citations. Since most of the references in the papers come from these papers, these papers have irreplaceable status and influence in the research field of image-based road crack detection algorithms.

Table 2 summarizes these most cited papers by reference, journal, country, year, citation, and average citation per year. The authors sort the papers based on the number of citations. "Deep convolutional neural networks with transfer learning for computer vision-based data-driven pavement distress detection" is the most cited paper. This paper, published in *Construction and Building Materials* in 2017, has received 652 citations. This paper is highly influential, with an average of 108.67 citations per year. In second place was "Automated pixel-level pavement crack detection on 3d asphalt surfaces using a deep-learning network" with 651 citations. This paper, published in *Computer-Aided Civil and Infrastructure Engineering* in 2017, had an average of 108.5 citations per year.

Table 2 provides a comprehensive analysis of these 25 papers, and Figure 4 generates a citation and average citation based on this dataset. The longer orange rectangles in the figure indicate more citations, while the longer blue rectangles indicate more average citations. A detailed analysis shows that most papers have been cited in a linear fashion over the years, but in Table 2, the citation and average citation of the papers [14,26–28] are much higher than the others, and even though the papers [26] were published in 2020, they received 470 citations, with an annual citation of 156.67, which clearly shows that [14,26–28] these papers will make an excellent contribution to this research area. Papers [29–33] have also received attention from researchers in a shorter period of time with a high average citation. On the other hand, papers [34–38] are at the bottom of the list in terms of both citation and average citation, and their low average citation (fewer than 30 times per year) indicates that these papers have not received enough attention from researchers.

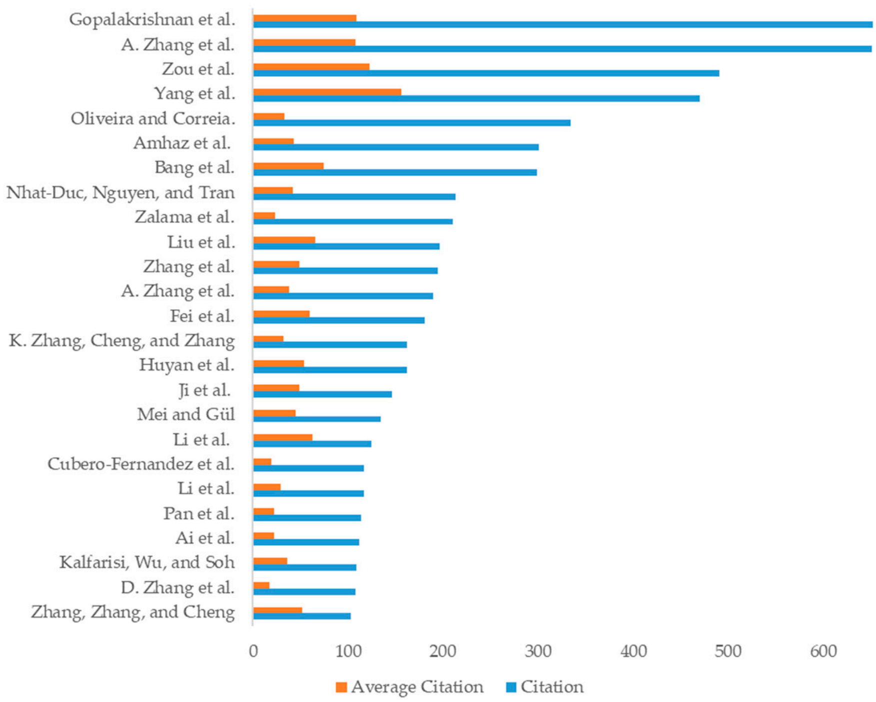


**Figure 4.** Summary of the most frequently referenced academic papers [14,26–49].

**Table 2.** Summary of the most frequently referenced academic papers.

| Reference | Journal | Country | Year | Citation | Average Citation per Year |
|---|---|---|---|---|---|
| [14] | Construction and Building Materials | USA | 2017 | 652 | 108.67 |
| [27] | Computer-Aided Civil and Infrastructure Engineering | China | 2017 | 651 | 108.50 |
| [28] | IEEE Transactions on Image Processing | China | 2019 | 491 | 122.75 |
| [26] | IEEE Transactions on Intelligent Transportation Systems | USA | 2020 | 470 | 156.67 |
| [39] | IEEE Transactions on Intelligent Transportation Systems | Portugal | 2013 | 334 | 33.40 |
| [40] | IEEE Transactions on Intelligent Transportation Systems | France | 2016 | 301 | 43.00 |
| [41] | Computer-Aided Civil and Infrastructure Engineering | South Korea | 2019 | 299 | 74.75 |
| [42] | Automation in Construction | Vietnam | 2018 | 213 | 42.60 |
| [43] | Computer-Aided Civil and Infrastructure Engineering | Spain | 2014 | 210 | 23.33 |
| [30] | Computer-Aided Civil and Infrastructure Engineering | Australia | 2020 | 197 | 65.67 |
| [44] | Computer-Aided Civil and Infrastructure Engineering | USA | 2019 | 195 | 48.75 |
| [45] | Journal of Computing in Civil Engineering | China | 2018 | 190 | 38.00 |
| [31] | IEEE Transactions on Intelligent Transportation Systems | USA | 2020 | 181 | 60.33 |
| [32] | Structural Control and Health Monitoring | China | 2020 | 162 | 54.00 |
| [46] | Journal of Computing in Civil Engineering | USA | 2018 | 162 | 32.40 |
| [47] | Automation in Construction | China | 2020 | 146 | 48.67 |
| [48] | Construction and Building Materials | Canada | 2020 | 135 | 45.00 |
| [33] | Construction and Building Materials | China | 2121 | 125 | 62.50 |
| [36] | Eurasip Journal on Image and Video Processing | Spain | 2017 | 117 | 19.50 |
| [37] | IEEE Transactions on Intelligent Transportation Systems | China | 2019 | 117 | 29.25 |
| [38] | IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing | China | 2018 | 114 | 22.80 |
| [34] | IEEE Access | Singapore | 2018 | 112 | 22.40 |
| [49] | Journal of Computing in Civil Engineering | USA | 2020 | 109 | 36.33 |
| [35] | Image and Vision Computing | China | 2017 | 108 | 18.00 |
| [29] | IEEE Transactions on Intelligent Transportation Systems | USA | 2021 | 103 | 51.50 |

### *4.2. Influential Journals, Authors, and Countries*

#### 4.2.1. The Most Productive Journals

In this subsection, the authors have listed the journals that have made outstanding contributions to the field of image-based road crack detection algorithms. A total of 122 different journals published the collected 305 papers. The authors extracted the top 10 publication sources based on the number of papers published. These 10 journals published a total of 124 (40.66%) of the 305 papers. The remaining 181 (59.34%) papers were published in the other 112 journals. Table 3 summarizes these most cited journals by journal name, total publications, total citations, average citations, impact factor, 5-year impact factor, publisher, and H-index. The authors have sorted the table according to the number of papers. Table 3 shows that the journal *IEEE Transactions on Intelligent Transportation Systems* holds the top position, with 21 papers and 1817 citations. The impact factor (IF) of this journal is also quite high, at 21.47. The H-index of this journal is 13, which indicates that this journal is very influential among researchers. The journal *Automation in Construction* ranks second, with 19 papers and 1138 citations.

**Table 3.** Summary of the most productive journals.

| Journal Name | Total Publications | Total Citations | Average Citations | Impact Factor | 5-Year Impact Factor | Publisher | H-Index |
|---|---|---|---|---|---|---|---|
| IEEE Transactions on Intelligent Transportation Systems | 21 | 1817 | 21.36 | 21.47 | 62.21 | Institute of Electrical and Electronics | 13 |
| Automation in Construction | 19 | 1138 | 24.33 | 32.27 | 49.41 | Elsevier B.V. | 16 |
| International Journal of Pavement Engineering | 16 | 230 | 7.24 | 13.67 | 14.38 | Taylor and Francis Ltd. | 7 |
| Journal of Computing in Civil Engineering | 15 | 1095 | 12.43 | 0.00 | 60.50 | American Society of Civil Engineers | 14 |
| Construction and Building Materials | 13 | 1188 | 18.06 | 4.25 | 39.82 | Elsevier Ltd. | 8 |
| IEEE Access | 13 | 475 | 13.11 | 1.00 | 30.25 | Institute of Electrical and Electronics | 10 |
| Computer-Aided Civil and Infrastructure Engineering | 10 | 1673 | 29.58 | 9.75 | 104.29 | Blackwell Publishing Inc. | 7 |
| Applied Sciences (Switzerland) | 9 | 77 | 4.09 | 5.71 | 8.56 | MDPI AG | 4 |
| Sensors | 8 | 170 | 10.85 | 20.67 | 21.25 | MDPI | 5 |
| Journal of Transportation Engineering Part B: Pavements | 7 | 52 | 2.53 | 4.00 | 4.80 | ASCE | 5 |

The top two journals on the list have very high values. The third-ranked journal, *International Journal of Pavement Engineering*, has 16 total publications, but only 230 total citations, while the other journals in the top 7 generally have more than 1000 total citations. The sixth-ranked journal, *IEEE Access*, has the same problem, with 13 total publications, but only 475 total citations. It is also interesting to note that the fourth-ranked journal, *Journal of Computing in Civil Engineering*, has an impact factor of 0 for the last two years, but a 5-year impact factor of 60.5. Other journals have fewer than 10 publications, and the number of citations is generally very low, indicating that researchers in the field of vision-based road crack detection have not paid much attention to these journals.

To understand trends in citations and impact, the authors were interested in journals with the lowest number of publications but high citation rates, so the authors searched the dataset for the existence of such journals. The authors found journals such as *EURASIP*

*Journal on Image and Video Processing* (1 paper, 117 citations), *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* (1 paper, 114 citations), *Image and Vision Computing* (1 paper, 108 citations), and *Structural Control and Health Monitoring* (2 papers, 175 citations).

To understand the historical development of the top journals in terms of paper publication and citation, the authors summarize the information in Table 4. Table 4 shows that all journals started to publish papers on image-based road crack detection around 2020. Before that, from 2013 to 2019, the number of papers published by these journals did not exceed 10 per year. However, there are still several journals with very high citation counts during these years, such as *IEEE Transactions on Intelligent Transportation Systems* in 2013, *IEEE Transactions on Intelligent Transportation Systems* in 2013, *IEEE Transactions on Intelligent Transportation Systems* in 2016, *Construction and Building Materials* in 2017, and *Computer-Aided Civil and Infrastructure* in 2017. *Computer-Aided Civil and Infrastructure Engineering* in 2017 and *Computer-Aided Civil and Infrastructure Engineering* in 2019 had more than 300 citations each.

**Table 4.** Historical development of the journals in terms of the publications and citations.

| Journal Name | 2013 | | 2014 | | 2015 | | 2016 | | 2017 | | 2018 | | 2019 | | 2020 | | 2021 | | 2022 | | 2023 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** | **P** | **C** |
| IEEE Transactions on Intelligent Transportation Systems | 1 | 334 | 0 | 0 | 0 | 0 | 1 | 301 | 0 | 0 | 0 | 0 | 1 | 117 | 2 | 651 | 1 | 103 | 11 | 302 | 4 | 9 |
| Automation in Construction | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 298 | 1 | 83 | 3 | 307 | 2 | 95 | 5 | 135 | 6 | 220 |
| International Journal of Pavement Engineering | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 25 | 9 | 195 | 6 | 10 |
| Journal of Computing in Civil Engineering | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 172 | 3 | 175 | 4 | 506 | 1 | 97 | 3 | 145 | 0 | 0 | 0 | 0 | 0 | 0 |
| Construction and Building Materials | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 98 | 1 | 652 | 0 | 0 | 0 | 0 | 5 | 282 | 2 | 139 | 1 | 9 | 3 | 8 |
| IEEE Access | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 112 | 1 | 63 | 5 | 211 | 4 | 87 | 0 | 0 | 2 | 2 |
| Computer-Aided Civil and Infrastructure Engineering | 0 | 0 | 2 | 292 | 0 | 0 | 0 | 0 | 1 | 651 | 0 | 0 | 2 | 494 | 1 | 197 | 0 | 0 | 1 | 27 | 3 | 12 |
| Applied Sciences (Switzerland) | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 37 | 4 | 31 | 3 | 9 |
| Sensors | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 46 | 3 | 105 | 3 | 19 |
| Journal of Transportation Engineering Part B: Pavements | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 18 | 1 | 10 | 0 | 0 | 0 | 0 | 2 | 12 | 2 | 5 | 1 | 7 |

P represents the number of papers published, while C represents the number of citations received by each paper.

#### 4.2.2. The Most Productive Authors

This subsection discusses the most productive authors in the research field of image-based road crack detection algorithms. In the dataset collected by Scopus, 305 papers involved 1046 authors. In this study, the top ten authors are selected based on the number of publications (five authors) and citations (five authors). Table 5 shows the top ten authors by author name, total publications, total citations, average citations, as first author, H-index, and country.

**Table 5.** Summary of the most productive authors.

| | Author Name | Total Publications | Total Citations | Average Citations | As 1st Author | H-Index | Country |
|---|---|---|---|---|---|---|---|
| **Based on Publications** | Huyan, Ju | 15 | 489 | 9.65 | 5 | 9 | China |
| | Li, Wei | 13 | 447 | 8.63 | 4 | 8 | China |
| | Wang, Kelvin C.P. | 9 | 1378 | 26.18 | 0 | 7 | USA |
| | Gu, Xingyu | 9 | 348 | 21.63 | 0 | 7 | China |
| | Li, Gang | 8 | 113 | 4.52 | 6 | 4 | China |
| **Based on Citations** | Wang, Kelvin C.P. | 9 | 1378 | 26.18 | 0 | 7 | USA |
| | Chen, Cheng | 7 | 1373 | 37.89 | 3 | 7 | China |
| | Zhang, Allen | 6 | 1345 | 38.35 | 4 | 6 | USA |
| | Fei, Yue | 5 | 1319 | 45.36 | 1 | 5 | USA |
| | Li, Joshua Q. | 4 | 1281 | 53.31 | 0 | 4 | USA |

The first part of Table 5 lists the top 5 authors with the most published papers. According to the summarized table, the maximum number of papers published by a single author is 15. “Huyan, Ju” and “Li, Wei” have published 15 and 13 papers, respectively, and hold the top two positions by a wide margin. Interestingly, “Wang, Kelvin C.P.” has published nine papers, none of them as first author, and has accumulated 1378 citations, significantly more than the other four authors. This indicates that “Wang, Kelvin C.P.” has played a significant role in the research. Although “Li, Gang” only ranked fifth in terms of number of publications, he is the first author in six, which was the highest among all authors. In terms of the number of published papers, the high-producing authors are mainly from China, which means that Chinese researchers have made important contributions to the field of image-based road crack detection.

The second part of Table 5 lists the five most cited authors. The table shows that all five authors have exceptionally high total and average citations, with over 1200 total citations and over 26 average citations. “Li, Joshua Q.” demonstrates the outstanding impact of this researcher with 53.31 average citations and a total citation count of 1281, which is lower by only 97 citations than the top-ranked “Wang, Kelvin C.P.” Four of the top five authors by extracted citations are from the United States, highlighting the current importance of USA researchers in the field of image-based road crack detection.

#### 4.2.3. The Most Productive Countries

In this subsection, the authors aim to investigate the most prominent countries in the field of research on image-based crack detection methods for roads. The analysis of the 305 papers filtered from the Scopus dataset revealed a total of 43 countries. Figure 5 shows the distribution of these 305 papers. In this figure, larger circles indicate that more papers have been published in that country. The authors analyzed the contribution of each continent in terms of published papers, with Asia having the highest contribution, publishing 63.24% of the total number of papers. North America and Europe accounted for 17.40% and 13.73% of the total number of papers, respectively, while the remaining 5.63% came from other regions of the world.

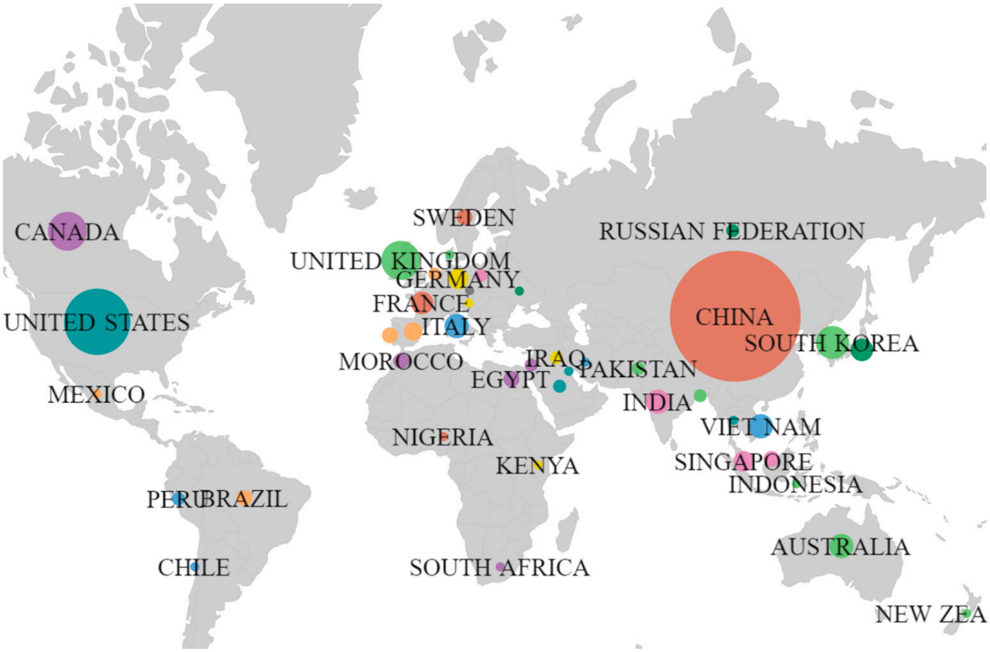


**Figure 5.** Geographical distribution of the publications.

After showing the geographical distribution of the papers in the dataset, the authors present the top 10 papers by number of publications in Table 6. Table 6 shows information on country, total publications, total citations, average citations, number of cited papers greater than or equal to 100/50/30/10, and H-index, arranged based on the number of papers published in each country. From Table 6, China is far ahead of other countries with a total of 203 papers, 6749 total citations, and an amazing H-index of 41. Although the United States is not as good as China in terms of number of publications or citations, it is in first place in terms of average citations (21.10). Both China and the United States have more than 10 papers with more than 100 citations. With 18 papers, Canada and the United Kingdom are tied for third place, but Canada's total citations of 776 are significantly higher than the United Kingdom's 338, Canada has 6 papers with more than 50 citations, while the United Kingdom has none.

**Table 6.** Summary of the most productive countries.

| Country | TPs | TCs | ACs | ≥100 | ≥50 | ≥30 | ≥10 | H-Index |
|---|---|---|---|---|---|---|---|---|
| China | 203 | 6749 | 10.12 | 13 | 22 | 20 | 58 | 41 |
| United States | 52 | 4996 | 21.10 | 15 | 7 | 7 | 13 | 29 |
| Canada | 18 | 776 | 11.72 | 4 | 2 | 1 | 7 | 13 |
| United Kingdom | 18 | 338 | 5.80 | 0 | 0 | 3 | 10 | 10 |
| South Korea | 13 | 707 | 15.97 | 2 | 1 | 3 | 3 | 9 |
| France | 8 | 505 | 10.98 | 0 | 2 | 1 | 1 | 5 |
| Italy | 8 | 251 | 9.55 | 0 | 3 | 3 | 0 | 7 |
| Australia | 7 | 393 | 16.82 | 1 | 1 | 1 | 3 | 6 |
| Vietnam | 7 | 402 | 12.81 | 1 | 1 | 0 | 3 | 6 |
| India | 7 | 55 | 4.83 | 0 | 0 | 2 | 1 | 4 |

TPs (total publications), TCs (total citations), ACs (average citations).

The authors also found that there are some countries in the dataset that do not appear in the top 10, but their papers received a high number of citations, indicating that the papers published in these countries also have a high impact. For example, in the dataset, Portugal has only three papers with 454 citations, and Malaysia has only three papers with 221 citations. These two countries have even more total citations than some of the top 10 countries.

### 4.3. Science Mapping Analysis

#### 4.3.1. Co-Citation Analysis

The authors considered co-citation analysis to be one of the science mapping techniques. Paper C simultaneously cites published papers A and B, resulting in co-citation. In this subsection, the authors perform co-citation analysis on cited sources and cited authors to explore journal-to-journal and author-to-author correlations. When citing two sources or authors simultaneously, it means that they have the same field of research and interest.

First, to analyze the co-citation network of cited sources, the authors set a threshold of at least 70 citations and finds 20 sources that meet this threshold. Table 7 lists the total co-citation link strength of these sources. The authors sort the table based on the total link strength of the journal. A source's total link strength is the sum of its link strengths with all other sources, while link strength refers to the frequency of co-citations between two sources in a third source.

**Table 7.** Co-citation indices of the sources.

| Source | Citations | Total Link Strength |
|---|---|---|
| Computer-Aided Civil and Infrastructure Engineering (comput-aided civ inf) | 607 | 10694 |
| IEEE Transactions on Intelligent Transportation Systems (ieee t intell transp) | 483 | 9144 |
| Proceedings CVPR IEEE (proc cvpr ieee) | 443 | 8626 |
| Automation in Construction (automat constr) | 434 | 8425 |
| Journal of Computing in Civil Engineering (j comput civil eng) | 285 | 5571 |
| Construction and Building Materials (constr build mater) | 322 | 5315 |
| Lecture Notes in Computer Science (lect notes comput sc) | 236 | 4957 |
| arXiv (arxiv) | 225 | 4472 |
| IEEE Transactions on Pattern Analysis and Machine Intelligence (ieee t pattern anal) | 221 | 4335 |
| IEEE International Conference on Image Processing (ieee image proc) | 221 | 4152 |
| IEEE Access (ieee access) | 180 | 3714 |
| Sensors (sensors-basel) | 176 | 3233 |
| IEEE Conference on Computer Vision and Pattern Recognition (ieee i conf comp vis) | 126 | 2919 |
| IEEE Transactions on Image Processing (ieee t image process) | 115 | 2339 |
| Transportation Research Record (transport res rec) | 132 | 2180 |
| Pattern Recognition Letters (pattern recogn lett) | 109 | 2066 |
| International Journal of Pavement Engineering (int j pavement eng) | 109 | 2012 |
| Advances in Neural Information Processing Systems (adv neur in) | 73 | 1530 |
| Advanced Engineering Informatics (adv eng inform) | 78 | 1498 |
| Measurement Science and Technology (measurement) | 72 | 1470 |

To better illustrate the link model, the authors generated the scientific landscape of the co-citation networks of the journals using the VOSviewer 1.6.20 software (Figure 6).

Figure 6 divides the journal into two clusters (red and green), with each node in Figure 6 representing the corresponding source. The larger the node, the higher the co-citation, and the thicker the link between two nodes, the stronger the link strength between the two sources. The authors chose the total link strength as the weight for the co-citation analysis. Sources with higher citations have higher link strength, and it is interesting to note that all sources of each cluster are cited together with the sources of the clusters they are in.

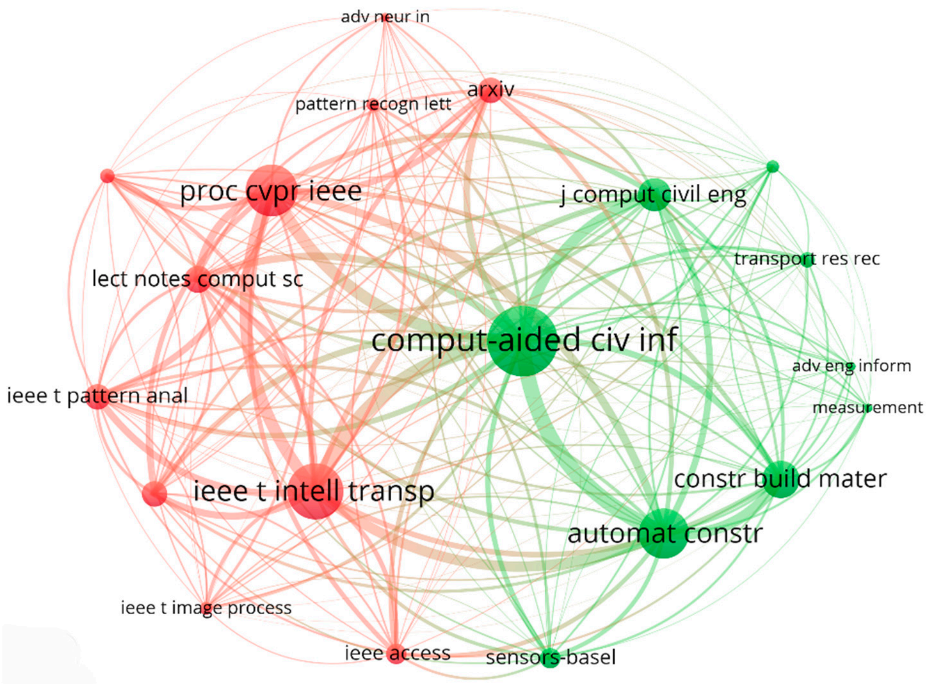


**Figure 6.** Network visualization of co-citation analysis of the sources.

A closer look reveals that the red cluster contains a total of 11 sources, the most prominent of which is *IEEE Transactions on Intelligent Transportation Systems* with 19 links and a total link strength of 9144. It has 134 citations for *Computer-Aided Civil and Infrastructure Engineering*, 115 citations for *Proceedings CVPR IEEE*, and 113 citations for *Automation in Construction*. This clearly shows that *IEEE Transactions on Intelligent Transportation Systems* is highly relevant to these three journals in the field of vision-based road crack detection research. Meanwhile, *Proceedings CVPR IEEE* has the second-highest total link strength in the red cluster with 8626.

The green cluster is composed of nine sources. The most influential source in the cluster is *Computer-Aided Civil and Infrastructure Engineering* with 19 links and a total link strength of 10,694. The journal is related to *IEEE Transactions on Intelligent Transportation Systems* with 134 citations and *Automation in Construction* with 134 citations. *Automation in Construction* is the second-most cited source in the green cluster with a total link strength of 8425.

After analyzing the co-citation network of the cited sources, the authors analyzed the co-citation network of the cited authors. To filter the top 20 authors in terms of total link strength, the citation threshold is set to at least 46 citations. Table 8 shows the total co-citation link strength of the cited authors. The total link strength of the authors determines the order of this table. For better understanding, we have generated the scientific landscape of the cited authors' co-citation network using the VOSviewer 1.6.20 software, as shown in Figure 7.

As can be seen in Figure 7, the cited authors are grouped into a total of three clusters (red, green, and blue). Each node represents the corresponding cited author: the larger the node, the higher the citation, and the thicker the line between two nodes, the stronger the link strength between the two cited authors. The total link strength is also chosen as the weight of the co-citation analysis, and the cited author with a higher citation has a higher link strength. The cited authors were cited together with the others cited author of the cluster in which they are located.

**Table 8.** Authors' co-citation indices.

| Cited Author | Citations | Total Link Strength |
|---|---|---|
| Zou, Qin (zou, q) | 157 | 1118 |
| Zhang, Allen (zhang, a) | 138 | 888 |
| Cha, Youngjin (cha, yj) | 124 | 875 |
| Shi, Yong (shi, y) | 96 | 749 |
| He, Kaiming (he, km) | 88 | 659 |
| Zhang, Lei (zhang, l) | 89 | 641 |
| Fan, Zhun (fan, z) | 75 | 584 |
| Oliveira, Henrique (oliveira, h) | 87 | 571 |
| Yang, Fang (yang, f) | 74 | 567 |
| Ronneberger, Olaf (ronneberger, o) | 74 | 560 |
| Long, Jonathan (long, j) | 56 | 498 |
| Amhaz, Rabih (amhaz, r) | 65 | 489 |
| Hoang, Nhat-Duc (hoang, nd) | 78 | 438 |
| Badrinarayanan Vijay (badrinarayanan, v) | 51 | 426 |
| Li, Qingquan (li, qq) | 57 | 388 |
| Girshick, Ross (girshick, r) | 50 | 378 |
| Lin, Tsung-Yi (lin, ty) | 46 | 343 |
| Tong, Zheng (tong, z) | 60 | 316 |
| Redmon, Joseph (redmon, j) | 48 | 306 |
| Gopalakrishnan, Kasthurirangan (gopalakrishnan, k) | 52 | 286 |

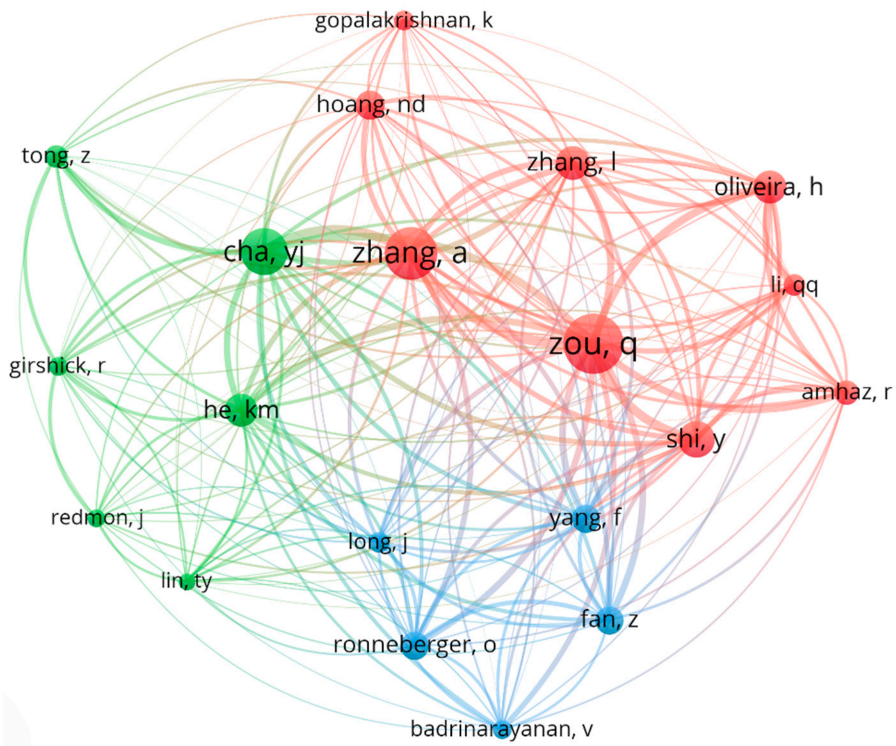


**Figure 7.** Network visualization of co-citation analysis of the cited authors.

The red cluster contains 9 authors. The lead author of this cluster is "Zou, Qin" with a total link strength of 1118. This author has the highest number of citations with 157. The second author is "Zhang, Allen" with a total link strength of 888 and 138 citations. The third author is "Shi, Yong" with a total link strength of 749 and 96 citations. "Zou, Qin" and "Zhang, Allen" have 49 citations together. Allen" and "Shi, Yong" are cited together 68 times, and "Zou, Qin" and "Shi, Yong" are cited together 33 times. "This suggests a high degree of similarity in the focus of their research topics. There is a higher correlation between the authors of the red clusters than between the authors of the red clusters and the authors of the other color clusters.

The green cluster has six authors. The most cited author in this cluster is “Cha, Youngjin” with a total link strength of 875. This author has the highest link strength with “Zou, Qin” with a value of 41 and also has a higher link strength with “Zhang, Allen” with a value of 37. Another influential author in this cluster is “He, Kaiming” with a total link strength of 659.

The blue cluster has five authors. The influence of the authors in this cluster is lower than that of the other two clusters, and the most influential author is “Fan, Zhun” with a total link strength of 584. This indicates that while the research directions of the cited authors in the blue cluster are pertinent to vision-based road crack detection, their collective citations have not increased significantly over time.

### 4.3.2. Co-Authorship Analysis

Collaboration in research plays a pivotal role in the generation of innovative ideas and their implementation in a more streamlined and expeditious manner. This is due to the inherent difficulty in completing a research task by a single individual. Another bibliometric measure employed in this work is co-authorship analysis. In this section, the authors will conduct a co-authorship analysis using the country as the unit of analysis to study the collaborative relationship between authors from different countries. In the case of the co-authorship analysis of the countries, the authors set a threshold of 10 for the minimum number of papers in each country and in Table 9 list the countries sorted by total link strength. The authors generated the scientific landscape of the co-authorship network of the countries using the VOSviewer 1.6.20 software, as shown in Figure 8.

**Table 9.** Co-authorship indices of the countries.

| Country | Documents | Total Link Strength |
|---|---|---|
| China | 189 | 43 |
| United States | 39 | 21 |
| Canada | 15 | 11 |
| South Korea | 11 | 8 |
| United Kingdom | 13 | 7 |

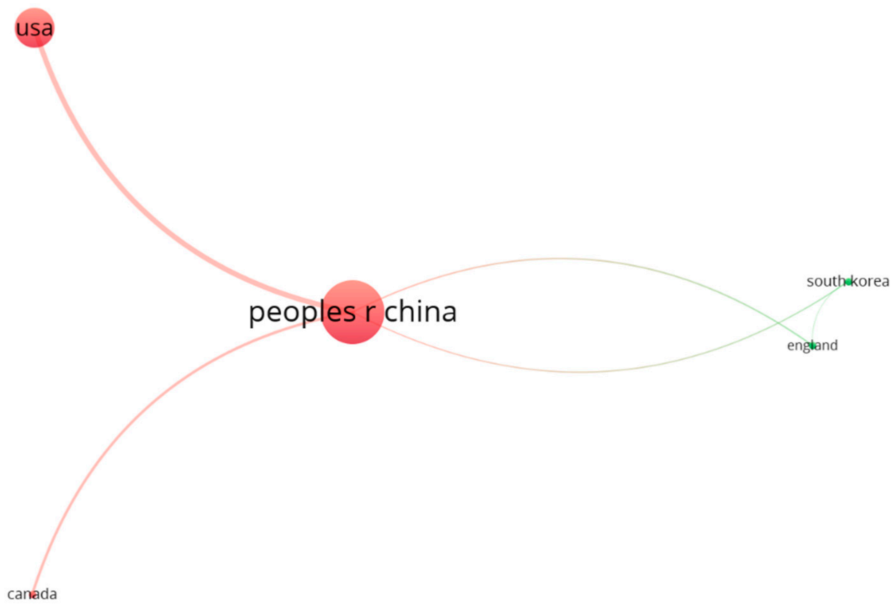


**Figure 8.** Network visualization of co-authorship of the countries.

Figure 8 categorizes countries into two distinct clusters, represented by the colors red and green. Each node in Figure 8 represents a country. The size of a node is indicative of the number of authors from that country who receive citations. The greater the thickness of the connecting line between the two countries, the more substantial the connection between them. The red cluster is comprised of a total of three countries. Among the countries in the red cluster, China is in the leading position, with a total link strength of 43. China is situated at the center of Figure 8 and has collaborated with the remaining four countries. This indicates that China occupies a pivotal position in this field. China has the greatest number of collaborations with the United States, with 21. The next most influential country in the red cluster is the United States, with a total link strength of 21. The United States only engages in collaborative activities with China. Canada, with a total link strength of 11, also cooperates only with China, with several collaborations of 11. In the green cluster, there are only two countries, South Korea and the United Kingdom, that cooperate closely with China in addition to each other.

#### 4.3.3. Co-Occurrence and Timeline View Analysis

Keywords in a research paper serve an essential function in elucidating a paper's research focus. In this section, the authors conducted a co-occurrence analysis of keywords to analyze the research trends and to identify and research hotspots in the field of image-based road crack detection algorithms. A total of 815 keywords were obtained from 305 publications using VOSviewer 1.6.20. The authors established a threshold of 10 for the minimum number of occurrences of a keyword. A total of 25 of the 815 keywords met the threshold. Figure 9 presents a network visualization of the paper's keyword co-occurrences. And Figure 9 is summarized in Table 10.

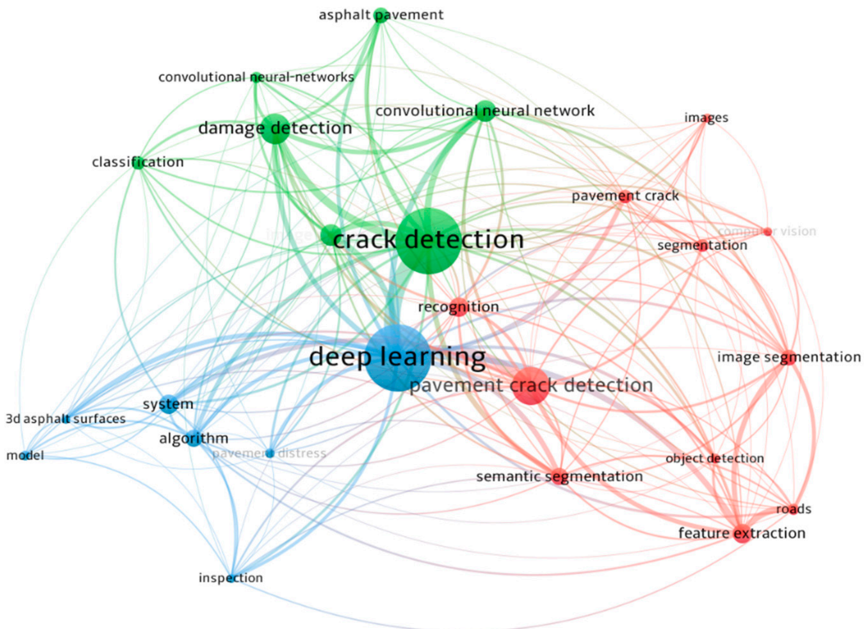


**Figure 9.** Network visualization of co-occurrences of the keywords.

The circular nodes depicted in Figure 9 represent distinct keywords. The size of the nodes indicates the frequency of occurrence of the keywords. Therefore, the larger the node, the more frequently and importantly the keyword is used. The size of the circle indicates the frequency of occurrence of the keyword in the paper. A smaller circle indicates a lower frequency of occurrence. The line between two nodes represents the number of times the two keywords appear together. The thicker the line, the more often the two keywords appear together in a paper. Conversely, the thinner the line between two nodes, the less often the two keywords appear together. Figure 9 illustrates that "deep learning" is the most frequently occurring keyword, appearing 72 times. The second most frequently occurring keyword is "crack detection", which appears 71 times. The third-ranked keyword is "pavement crack detection", which has appeared 41 times. It is noteworthy that two keywords with a high degree of similarity, namely "convolutional neural network" and "convolutional neural networks", were identified during the keyword analysis process. When combined into a single keyword, it ranks fourth with 35 occurrences. The keyword "damage detection" was identified 33 times and ranked fifth. The node "deep learning" is most closely associated with "crack detection", "pavement crack detection", and "damage detection", as evidenced by the thickest connecting lines between these three nodes. Deep learning is a widely used technique in road crack detection.

**Table 10.** Summary of clusters obtained from keyword analysis.

| Cluster Color | Observed Keywords | No. of Keywords |
|---|---|---|
| Red | computer vision, feature extraction, image segmentation, images, object detection, pavement crack, pavement crack detection, recognition, roads, segmentation, semantic segmentation | 11 |
| Green | asphalt pavement, classification, convolutional neural network, convolutional neural-networks, crack detection, damage detection, image processing | 7 |
| Blue | 3d asphalt surfaces, algorithm, deep learning, inspection, model, pavement distress, system | 7 |

Figure 9 illustrates that the red cluster, comprising 11 keywords, is the largest of the three clusters. The keyword "pavement crack detection" is the largest for the nodes in the red cluster. This keyword is observed 41 times. The other keywords with a greater number of occurrences in this cluster are "feature extraction" and "image segmentation", with 21 and 17 occurrences, respectively. The keywords in the red cluster underscore the significance of feature extraction and image segmentation techniques in the recognition and analysis of road conditions. The primary keyword in the green cluster is "crack detection" which occurs a total of 71 times, along with "damage detection", "convolutional neural network" and "image segmentation" which occur 21, 17, and 17 times, respectively. The combination of "convolutional neural network" and "image processing" serves to highlight the significance of employing convolutional neural network techniques in the context of damage detection and image processing. The keyword "deep learning" is the most prominent in the blue cluster, occurring 72 times and representing the most notable keyword in Figure 9. The keywords in the blue cluster collectively emphasize the pivotal role of deep learning in enhancing algorithmic efficiency, model accuracy, and overall system performance, particularly in an environment where complex data analysis is a significant consideration.

Following the completion of the cluster analysis, the authors proceeded to extract the 10 most frequently occurring keywords. Table 11 provides a summary of the keywords, frequency, links, and total link strength. The table was sorted by keyword frequency. The keywords contained within Table 11 are analyzed and the keywords "deep learning", "crack detection", "pavement crack detection" and "recognition" all have links of nine, which is associated with all other keywords in the table. This indicates that these keywords are the core keywords in the field of image-based road crack recognition. It is noteworthy that although the keyword "recognition" is associated with the remaining nine keywords, the total link strength is only 32. This indicates that it does not appear to be a highly interconnected keyword with other keywords.

In addition, the study's authors employed the CiteSpace 6.3.R2 software to enumerate the keywords that appeared with a frequency exceeding a specified threshold. Figure 10 presents a timeline view of the keywords. This shows the trajectory of research and development in the field of image-based road crack recognition from 2013 to 2023. The time distribution can be divided into three stages. In the initial stage, spanning from 2013 to 2015, the most pivotal keywords were "crack detection", "image processing and recognition", "algorithm", and "system". At this stage, the researchers conducted a comprehensive investigation into the fundamental methodologies for crack detection on roads, with a particular emphasis on ensuring the high applicability of the developed models and methods. The second stage, spanning from 2015 to 2020, reveals a gradual increase in research on image-based road crack detection, with prominent keywords such as "deep learning", "pavement crack detection", "damage detection", and "convolutional neural network". This stage has witnessed the introduction of deep learning algorithms in numerous studies, resulting in notable advancements in the identification and classification of road cracks, thereby markedly enhancing detection reliability. In the third stage, spanning the years 2020 to 2023, the most common keywords are "feature extraction" and "semantic segmentation". The research conducted during this phase will facilitate the development of more sophisticated and accurate systems for monitoring and evaluating cracks in road surfaces. Table 12 presents a list of keywords related to image-based road crack detection, organized by three distinct periods.

**Table 11.** Summary of the top 10 keywords.

| Keyword | Frequency | Links | Total Link Strength |
|---|---|---|---|
| deep learning | 72 | 9 | 97 |
| crack detection | 71 | 9 | 82 |
| pavement crack detection | 41 | 9 | 51 |
| damage detection | 33 | 8 | 44 |
| convolutional neural network | 23 | 8 | 42 |
| image processing | 23 | 7 | 35 |
| feature extraction | 21 | 8 | 33 |
| recognition | 21 | 9 | 32 |
| system | 21 | 6 | 25 |
| semantic segmentation | 19 | 7 | 33 |

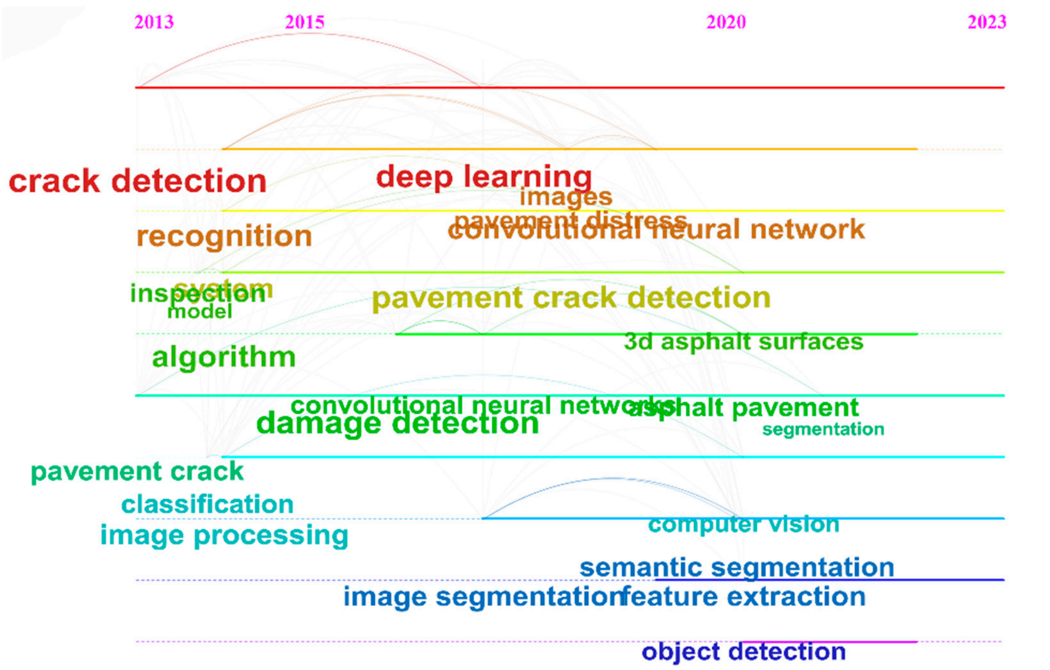


**Figure 10.** The timeline view of the keywords.

**Table 12.** The keywords of road crack detection-related publications occurred during three different periods.

| Periods | Keywords |
|---|---|
| 2013–2015 | crack detection, image processing, recognition, algorithm, system, classification, pavement crack, model, inspection |
| 2015–2020 | deep learning, pavement crack detection, damage detection, convolutional neural network, convolutional neural-networks, image segmentation, pavement distress, pavement distress, images |
| 2020–2023 | feature extraction, semantic segmentation, asphalt pavement, object detection, 3d asphalt surfaces, computer vision, segmentation |

## 5. Critical Analysis

By analyzing the previous review papers, and performing a co-occurrence and timeline view analysis of keywords, the authors found that the image recognition algorithm based on deep learning is receiving more and more attention from researchers. Therefore, it was decided to conduct further research on the road crack recognition algorithm based on deep learning technology, and a critical analysis of the related papers was conducted to further discover the related knowledge of the method. In the previous section, 72 papers that focused on deep learning-based road crack recognition were screened. Excluding the papers that did not provide the detailed process of realizing the research method, 65 papers were finally screened. The authors grouped these 65 papers based on the types of computer vision techniques used in them. The authors then analyzed the 65 papers based on the problem statement, methodology, and results. The following issues were raised.

Q1. What deep learning method does a paper use?
Q2. What backbone does the deep learning method use?
Q3. What deep learning framework does a paper use?
Q4. What datasets does a paper use?
Q5. What concrete surface does a paper consider?
Q6. What loss function does a paper use?
Q7. What optimizer does a paper use?
Q8. What annotation tool does a paper use?
Q9. What performance levels does a paper reach?

The answers to these questions are summarized in Tables 13–15 for papers in various categories.

**Table 13.** Summary of deep learning techniques for crack classification.

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [14] | DCNN | VGG-16 | Keras | LTPP | Asphalt pavement | - | Adam | - | Accuracy = 90%, Precision = 90%, Recall = 90%, F1-score = 90% Cohen's Kappa score = 74.2% |
| [50] | CNN | AlexNet | PyTorch | Own collection | Asphalt pavement | - | MBGD | - | Accuracy for transverse cracks = 80.6% Accuracy for longitudinal cracks = 79.2% Accuracy for alligator cracks = 91.3% |
| [51] | CNNs | VGG-16 | - | GSV | Asphalt pavement | Cross-Entropy | Adam | Manually | Accuracy = 97.2% |
| [8] | CNN | EfficientNet-B4 | - | Own collection | Asphalt pavement | Cross-Entropy | Adam | - | Accuracy = 99.32% |

**Table 13.** *Cont.*

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [9] | CP-YOLOX | CSPDarkNet-SPP | TensorFlow 2.5 | Own collection | pavement | - | Adam | LabelImg | Accuracy = 87.71%<br>mAP = 80.64 |
| [52] | CNN | - | - | Own collection | Asphalt pavement | Cross-Entropy | Adam | LabelImg | Accuracy = 94.14%<br>Precision = 94.52%<br>Recall = 94.43%<br>F1-score = 94.47% |
| [11] | CNNs | AlexNet<br>ResNet | - | Own collection | Asphalt pavement | Cross-Entropy | Adam | - | Accuracy = 87.5% |
| [53] | CNN | VGG-16 | Caffe | CCIC | pavement | Cross-Entropy<br>A Boundary<br>Box Regression | - | - | Accuracy = 98.217% |
| [54] | FS-Net | Darknet-53 | Pytorch 1.6 | Own collection | pavement | - | - | - | Precision = 94.30%<br>Recall = 0.74%<br>FNR = 93.35% |
| [55] | Faster R-CNN | ResNet | PyTorch | Own collection | Pavement | - | SGD | Manually | Average precision = 87.21%<br>Recall = 88.09% |
| [56] | YOLO V5 | - | Python 3.8 | Own collection | Asphalt pavement | - | SGD | Manually | mAP = 87.2% |
| [57] | YOLOv2 | - | matlab | Own collection | Concrete pavement | - | SGDM<br>Adam<br>RMSProp | Labeler | AP = 89% |
| [58] | MLC | - | PyTorch 1.5.0 | Own collection | Asphalt pavement | Cross-Entropy | - | - | Accuracy = 97%<br>F1-score = 93% |

'-' Denotes the paper did not provide the particular information.

**Table 14.** Summary of deep learning techniques for crack detection.

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [42] | CNN | - | MATLAB | Own collection | Asphalt pavement | - | SGDM | Labeler | CAR = 92.08%<br>TPR = 85%<br>TNR = 100%<br>FPR = 0%<br>FNR = 15%<br>Precision = 100%<br>Recall = 83% |
| [12] | DCNN | - | - | Own collection | Asphalt pavement | MSE | SGD | MATLAB | Accuracy = 94.36%<br>Maximum Length Error = 1 cm<br>MSE = 0.2377 |
| [59] | Bio-inspired Co-evolutionary DCNN | - | MATLAB | CRACK500 and GAPs384 | Road surfaces | - | - | - | Accuracy = 99.04%<br>Jaccard index = 98.42%<br>Loss error rate = 0.03<br>Precision = 99.25%<br>Recall: 99.24%<br>Prediction accuracy: 99.72% |
| [60] | YOLOv3 | Darknet-53 | PyTorch | Own collection | Asphalt pavement | Sum-Squared Error | - | LabelImg | Precision = 70%<br>Average IoU = 50.39% |
| [61] | CNN | - | TensorFlow | Own collection | Asphalt pavement | Cross-Entropy | - | LabelImg | Accuracy = 96% |
| [33] | YOLOv4<br>YOLOv5 | Darknet-53 | PyTorch | Own collection | Asphalt pavement | - | - | LabelImg | P = 0.974<br>R = 0.94<br>F1 = 0.83<br>mAP = 94.39% |
| [62] | CNN | ResNet | - | Own collection | Asphalt pavement | - | - | - | Accuracy = 95% |
| [63] | RetinaNet | ResNet | - | Own collection | Asphalt pavements | Focal | - | Manually | Accuracy = 96.5% |
| [64] | YOLOv5 | - | PyTorch | Own collection | Pavement | | | Roboflow | Precision = 95.27%<br>Recall = 83.45%<br>F1-Score = 88.96%<br>mAP = 91.81% |

**Table 14.** *Cont.*

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [65] | YOLOv5s | - | - | Own collection | Pavement | - | - | CVAT | F1-Score = 86.79% |
| [66] | YOLOv5 | - | PyTorch | RDD | Asphalt pavement | GIoU and Cross-Entropy | SGD | - | F1 = 67.39% |
| [67] | CCapFPN | - | - | PCD19, CFD, Crack500, CrackTree260, CRKWH100, CrackLS315 and Stone331 | Asphalt, concrete, and stone pavement | - | - | - | Presition = 91.21% Recall = 90.44% F1-Score = 90.82% |
| [68] | Faster R-CNN Mask R-CNN | ResNet | PyTorch 1.8 | CRACK500 | Pavement | Cross-Entropy | SGD | Manually | - |
| [15] | GCN | - | - | Own collection | Pavement | - | - | - | Precision = 84% Recall = 75.5% F1-Score = 77.2% |
| [69] | Segmentation R-CNN | - | TensorFlow | Own collection | Asphalt pavements | Cross-Entropy | SGD | Manually | IoUs = 87.6% |
| [70] | Mask R-CNN | ResNet-101 | Keras TensorFlow | Own collection | Asphalt pavements | - | Adam | Manually | Average accuracy = 92.10% |
| [71] | DDSNet | - | TensorFlow | Own collection | Pavement | - | Adam | LabelImg | mAP = 89.25% F-score = 96.18% FPS = 16.74 |
| [72] | CrackCLF | U-Net | PyTorch | CFD, Crack500 and Crack700 | Pavement | - | Adam | Manually | Precision = 94.51% Recall = 93.44% F1-Score = 94.06% |
| [73] | SegDecNet++ | U-Net | PyTorch | CFD, CRACK500, CrackTree200, DeepCrack, GAPs384, Rissbilder and Non-crack | Concrete | Cross-Entropy | Adam | Manually | Dice score = 81% IoU = 71% |
| [74] | CrackNet-M | - | TensorFlow | Own collection | 3d asphalt pavement | Focal | Adam | Manually | Precision = 94.28%, Recall = 93.89%, F-measure = 94.04% |
| [75] | SROCD | - | - | Shadow-Crack, GAPs384, Cracktree200, Crack500, CFD and AEL | Pavement | Cross-Entropy | - | Labelme | AIU = 0.514 ODS = 0.783 OIS = 0.846 |
| [76] | RCD-Net | - | TensorFlow | Crack500 | Pavement | Focal | SGD | - | Accuracy = 96.29% Dice Coefficient = 97.33% IoU = 96.90% |
| [77] | PCDM-HED | - | - | LS-3D, LCMS, ESAR and 2D-I | 3d pavement | Focal | - | - | Recall = 0.91% F-values = 0.89% |
| [78] | YOLOv5-CBoT | - | PyTorch | RDD | Pavement | - | SGD | - | Precision = 64.1% Recall = 59.3% F1-Score = 61.6% mAP = 63.7% |
| [79] | YOLOv4-Tiny | - | - | DeepCrack | Asphalt and concrete pavement | - | Adam | LabelImg | mAP = 54.88% |
| [80] | YOLO | Darknet19 ResNet50 | - | Own collection | Tiled sidewalks | - | SGD Adam | - | Accuracy = 94.54% |
| [81] | WOA | ResNet-18 | - | Own collection | Asphalt and concrete pavement | Cross-Entropy | SGD Adam | - | Accuracy = 97.16% |

'-' Denotes the paper did not provide the particular information.

**Table 15.** Summary of deep learning techniques for crack segmentation.

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [48] | ConnCrack | DenseNet121 | - | ImageNet, CFD EdmCrack600 | Asphalt pavement | cWGAN | - | - | Precision = 96.79% Recall = 87.75% F1 Score = 91.96% |
| [26] | FPHBN | - | - | CRACK500, GAPs384, Cracktree200, CFD Aigle-RN and ESAR and LCMS | Pavement | - | - | - | AIU = 0.560 ODS = 0.604 OIS = 0.635 |
| [32] | Crack U-Net | U-Net | TensorFlow | Own collection | Pavements | Pixelwise Cross-Entropy | Adam | - | Loss = 0.025 Accuracy = 99.01% Precision = 98.56% Recall = 97.98% F1-measure = 98.42% |
| [82] | DNN | DenseNet201 | - | CFD EdmCrack1000 | Pavement | - | - | - | Precision = 91.00% Recall = 93.22% F1 score = 91.99% |
| [31] | CrackNet-V | VGG | - | PaveVision3D | Asphalt pavement | Cross-Entropy | SGD | Manually | Precision = 84.31% Recall = 90.12% F1 Score = 87.12% |
| [83] | PAN | DenseNet121 | TensorFlow | Crack500, DeepCrack, GAPS384, MCD | Asphalt and concrete pavements | Cross-Entropy Dice | Adam | - | Dice = 0.7681, IoU = 0.6235 |
| [84] | APLCNet | ResNet | - | CFD GDPH | Pavement | Cross-Entropy | SGD | - | Precision = 92.21% Recall = 94.89% F1-Score = 93.53% AP = 16.5% |
| [85] | Xception | BiSeNet | TensorFlow | Crack500 | - | Cross-Entropy Dice | Nadam | - | F1 Score = 82.70% IoU = 73.79% |
| [86] | EDNet | ResNet-34 | Keras | PaveVison3D CFD | Pavement | Cross-Entropy | Adam | - | F1-score = 97.80% Precision = 97.36% Recall = 98.24% |
| [87] | multi-view stereo imaging+ U-Net | U-Net | MATLAB 2020a and Python 3.7 | Own collection | Asphalt roads | Cross-Entropy Dice | Adam | - | overall Precision = 96.32% Recall = 95.52% F1 score = 95.92% |
| [88] | CNN | DenseNet | PyTorch | AEL, Crack500 Cracktree200 | Pavement | Cross-Entropy | SGD | - | ODS = 0.627 OIS = 0.669 |
| [89] | DAUNet | U-Net | TensorFlow | CRACK500, GAPs384, CrackTree200, CFD, AEL | Pavement | Focal Dice | Adam SGD | Manually | ODS = 0.812 OIS = 0.831 |
| [90] | FIFD | - | TensorFlow | Own collection | Pavement | - | - | - | Recall = 91.0% Precision = 89.9% F1 score = 90.5% |
| [91] | WSIS | - | - | Own collection | Pavement | Cross-Entropy | - | - | Accuracy = 98% Precision = 84% Recall = 76% F1-sore = 80% |
| [92] | W-segnet | VGG16 | - | CFD, Crack500 CrackTree200 EdmCrack600 | Pavement | Dice | Adam | Labelme | MPA = 87.52% MioU = 75.88% |
| [10] | CNNs | VGG16 | TensorFlow | Own collection | Concrete structures | - | Adam | - | F1 score = 99.53% |
| [93] | PCDNet | - | PyTorch | Own collection | 3D asphalt surfaces | Cross-Entropy | Adam | - | Precision = 88.5% Recall = 90.2% F-1 score = 89.3% |
| [94] | DCANet-SE-ResNet | ResNet-50 | PyTorch | CFD Crack500 | Pavement | Cross-Entropy | SGD | Manually | Precision = 83.72% Recall =80.99% F1 score = 82.33% |
| [95] | EHRS-Net | - | - | CFD-ex HRSD | Pavement | Hybrid And Cross-Entropy | Adam | - | mPA = 93.35% mIoU = 78.33% |
| [96] | PSGCNN | - | TensorFlow | Crack500 DeepCrack GAPs384 | Pavement | Cross-Entropy, Tversky and Lovász hinge | Adam | Manually | Precision = 95.20%, Recall = 94.08%, and IoU = 89.82% |
| [97] | DeepLabv3+ | - | Pytorch 1.2.0. | Own collection | Concrete and asphalt pavements | Cross-Entropy | Adam | Manually | Precision = 91.75% Recall = 92.54% F1 score = 92.14% |

**Table 15.** *Cont.*

| Ref | Method | Backbone | Framework | Dataset | Surface | Loss Function | Optimizer | Annotation Tool | Performance |
|---|---|---|---|---|---|---|---|---|---|
| [98] | ECSNet | - | - | DeepCrack | Pavement | BCE With Logits | Adam | - | F1 score = 84.45%<br>IoU = 73.08%<br>FPS = 73.29 |
| [99] | STA | - | PyTorch | CFD<br>Crack 500<br>CrackSC | Asphalt and concrete pavement | Dice | SGD | Manually | Precision = 84.08%<br>F1 score = 87.08%<br>Recall = 90.79% |
| [100] | PSA-Net | ResNet-101 | PyTorch | Own collection | Asphalt and concrete pavement | Dice | Adam<br>SGD | - | Precision = 99.55%<br>Recall = 94.50%<br>Accuracy = 98.70%<br>F1-score = 96.44% |
| [101] | SegNet | - | PyTorch | DeepCrack<br>CFD<br>Crack500 | Pavement | Focal | SGD | - | MIoU = 87.53%<br>Precision = 87.67%<br>Recall = 85.41%<br>F1-score = 86.52% |

'-' Denotes the paper did not provide the particular information.

In this section, the authors categorize the deep learning-based image recognition algorithms in the field of road crack detection into three different categories according to their functions, namely, classification, detection, and segmentation. Classification involves identifying whether an image contains road cracks or the type of cracks. Detection not only identifies the presence of cracks, but more importantly, it determines the location of the cracks. Segmentation is more sophisticated in that it determines whether each pixel in the image belongs to a crack or not, not just the border region.

### 5.1. Classification

Gopalkrishnan et al. [14]. developed the deep convolutional neural network (DCNN) algorithm based on the VGG-16 backbone. The Federal Highway Administration (FHWA) and Long-Term Pavement Performance (LTPP) datasets were used to train the DCNN algorithm. It was also applied to hot mix asphalt (HMA) and Portland cement concrete (PCC) pavement images, and the highest accuracy of up to 90% was finally achieved using the Adam optimizer.

Li et al. [50]. proposed an unsupervised learning method for road crack classification. The method fuses a k-means clustering algorithm with a CNN, and the backbone of the method is AlexNet. The author created his own dataset using smartphones and digital cameras, and compared the method with the traditional method for classification experiments. The test results showed that the method has higher accuracy.

Maniat et al. [51]. investigated the feasibility of using Google Street View (GSV) to assess the quality of roads. The development of a CNN was specifically aimed at identifying road cracks in GSV. The author compared the results of the experiment with those of a commercial visual inspection company for road quality assessment. The results demonstrate the feasibility of intercepting GSV image datasets for road quality assessment.

Liu et al. [8]. investigated the combination of infrared imaging and deep learning for road crack detection. The team created a dataset containing three types of images: visible, infrared, and fusion (a combination of visible and infrared). Thirteen CNN models were tested and evaluated on this dataset. The test results show that infrared images have the highest accuracy and visible images have the lowest accuracy. The experiment demonstrates that the use of infrared imaging technology in road crack detection can significantly improve the detection accuracy.

Another paper by Liu et al. [52]. also combines infrared thermography and convolutional neural networks for crack detection in asphalt roads. The paper also categorized the images into visible, infrared, and fusion. The difference is that the experiment further tested the effectiveness of the image for transfer learning. The results of the experiment showed that the model trained from scratch performed best on the fusion image, while the transfer learning model performed well on the visible image. However, the experimental results only performed well on less severe cracks and were less accurate on more severe crack images.

Yang et al. [9]. developed a road crack detection method using 3D ground-penetrating radar with deep learning techniques. The method uses two models: CP-YOLOX for localizing anomalous waveforms and scattering vision transformer (SviT) for classifying these waveforms into distress categories. The authors compared the self-generated method with methods such as MobileNet and ResNet50 using their own collected dataset, and the results indicated that this method performed the best. The authors also found that a larger number of datasets can improve the accuracy and reliability of the method.

Hou et al. [11]. proposed a crack detection method based on images with small samples. Hou et al. preprocess the limited sample images in two steps to solve the problem of insufficient sample size and the complexity of image content. First, Hou et al. use the data enhancement technique to significantly expand the dataset, increase the number of images, and solve the data imbalance problem. Then, the original images are converted into binary black-and-white images to effectively reduce the complexity of image features. Next, the authors test the method in the AlexNet, SE-Net, and ResNet frameworks, and the experiments demonstrate its effective improvement of crack classification accuracy.

Ma et al. [53]. introduced a CNN for detecting small objects such as cracks. The method incorporates multiple feature layers to improve the detection capability. The method uses multi-scale feature extraction and anchor boxes with different aspect ratios to improve the speed and accuracy of crack detection. The method achieves an impressive speed of 96.6 frames per second with an accuracy of 98.217%, which is far better than the YOLOv1, YOLOv2, and fast region-based convolutional neural network (Fast R-CNN) algorithms.

Hou et al. [54]. proposed an FS-Net-based crack detection method for roads. To better capture crack features, the method uses flexible rectified linear units (FReLU) instead of the traditional leaky ReLU. To improve crack detection, maximum pooling is replaced by strip pooling. The authors perform training and testing on a self-generated dataset and compare it to R-CNN and YOLOv3. The test results show that the method has a faster processing speed than R-CNN and YOLOv3, but still has a high detection accuracy.

Ibragimov et al. [55]. proposed a faster region-based convolutional neural network (Faster R-CNN) for road crack detection. The model uses a regional proposal network (RPN) for crack detection, which is able to quickly detect targets of different sizes in a multi-target scenario. Different types of cracks are detected on a self-constructed dataset, and the results show that the method is able to detect and classify different cracks at a high level, effectively reducing the dependence on manual detection.

Wang et al. [56]. conducted an investigation into the integration of the vision transformer (ViT) module into the YOLOv5 model to enhance the accuracy of road crack detection. The method achieved a mean average precision (mAP) of 87.2% on a self-constructed dataset of 1944 images, and the detection process took only 11.9 ms per image. The test results demonstrate the effective application of the method in real-time road crack monitoring.

Maslan et al. [57]. used an unmanned aerial vehicle (UAV) to acquire a dataset, which they then combined with the YOLOv2 model to detect the dimensions of cracks in an airport runway and pinpoint their locations on the concrete surface. The YOLOv2 detector successfully identified cracks with high average precision (AP = 0.89), demonstrating its potential for real-world use. The system can effectively replace manual inspection, making the safety of airport runways safer and more efficient.

Espindola et al. [58]. suggest using architectures such as VGG16, ResNet-34, and ResNet-50 to explore multi-label classification (MLC) and convolutional neural networks (CNNs) to find cracks in the road. Tested on a self-generated dataset, the method achieves up to 97% accuracy and a 93% F1 score. The method effectively reduces the need for expensive sensors while reducing the need for manual image cropping, promoting more targeted and cost-effective classification. The method effectively eliminates the need for expensive sensors while reducing the need for manual image cropping, promoting more targeted and cost-effective pavement evaluation.

### 5.2. Detection

Nhat-Duc et al. [42]. established and compared the performance of two intelligent methods for automatic road crack detection, showing that the model based on the CNN algorithm significantly outperformed the traditional edge detection approaches. The CNN algorithm constructed a model with a classification accuracy rate (CAR) of 92.08%. The CNN algorithm constructed a model with a CAR of 92.08%.

Tong et al. [12]. conducted a study to assess the efficacy of DCNN in the automated identification of road crack length in batches. To extract the properties of the cracks, k-means clustering analysis was employed to convert the original RGB images into grayscale maps. The DCNN network was optimized using stochastic gradient descent (SGD). Following the training and testing phases, the results demonstrated that the algorithm achieved a recognition accuracy of 94.36%, with a maximum length error of 1 cm and a mean squared error (MSE) of 0.2377.

Alfarraj et al. [59]. used an IoT system with a bionic deep learning approach to improve the accuracy of road crack detection. The CRACK500 and GAPs384 datasets were employed to train the algorithm. Eventually, the algorithm's capabilities were confirmed, including the per-pixel accuracy (99.04%), Jaccard index (98.42%), loss error rate (0.03), precision (99.25%), recall (99.24%), and prediction accuracy (99.72%) metrics.

Opara et al. [60]. proposed to develop a method for road crack detection based on YOLOv3. The method is effective in recognizing longitudinal cracks, transverse cracks, alligator cracks, and potholes. The authors collected their own dataset for experimentation, and the results demonstrated a precision of 70% and an average IoU of 50.39%. The results demonstrate that the method exhibits high accuracy in the field of road crack recognition.

Han et al. [61]. proposed a CNN for the purpose of learning crack features from images that do not require any preprocessing. They employed their own image dataset, collected from open-source sources, for training purposes. This dataset was based on the open-source TensorFlow framework developed by the Google Brain team. The experimental results indicate that the method exhibits satisfactory performance.

Li et al. [33]. proposed a crack detection system based on deep learning models and 3D ground-penetrating radar (GPR). The method employs GPR to construct a dataset. The YOLOv4 and YOLOv5 models were employed for training and detection purposes on this dataset. Experimental results indicate that the YOLOv4 and YOLOv5 models exhibit a notable advantage over the YOLOv3 model in the context of training on a limited sample size dataset. The mAP of YOLOv5 is 94.39%.

Chun et al. [62]. developed a CNN framework that focuses on training image types that are difficult to detect in order to improve the training performance of the framework. The approach eschews the traditional method of increasing the number of training images and recursively improves this model's accuracy by collecting and analyzing images with recognition errors and retraining the CNN. The experimental results indicate that the accuracy of the model is up to 95%.

Tran et al. [63]. proposed a network model with supervised learning capabilities, which is able to detect cracks and lane markings. The model is based on the ResNet network and employs a feature pyramid network (FPN) for feature extraction. To train and test the network, the authors enhanced 1000 images to 20,000 images using image enhancement techniques. The experimental results demonstrate that the model exhibits a high degree of accuracy, with a rate of 96.5%.

Ren et al. [64]. selected YOLOv5 as the foundation for developing road crack detection methodologies. To enhance the accuracy of YOLOv5, the researchers incorporated additional attention modules, including SENet, ECANet, CBAM, and CoordAtt. A self-constructed dataset is employed in comparative experiments on different crack detection models. In all aspects of the experimental results, the accuracy of YOLOv5 with the added attention mechanism outperforms that of YOLOv3, YOLOv4, and Faster CNN. The method is an effective means of enhancing the accuracy of YOLOv5.

Yang et al. [65]. proposed a novel annotation methodology, a dense and redundant annotation method, with the objective of enhancing the efficiency of data collection and reducing the time required for data collection in the process of road crack recognition. The method initially labels 800 images manually and then employs the trained initial model for training on a larger sample dataset. Following repeated correction and retraining of the misrecognized images, the total weight achieved a satisfactory experimental result. The method reduces the overall training time by 80%. This author tested 13 mainstream target detection methods and found that the method can still obtain good accuracy with a significant increase in training speed.

Xiang et al. [66]. proposed a novel approach to enhance the road crack detection capability by combining the YOLOv5 architecture with the transformer module. The transformer's capacity to capture long-range dependencies enables the effective improvement of detection accuracy. The method was tested on an RDD dataset and compared with eight existing state-of-the-art methods, including Faster R-CNN, EfficientDet, YOLOv4, etc. It achieved high F1 scores, marking a significant advancement in the field of road maintenance technology.

Yu et al. [67]. proposed the context-augmented capsule feature pyramid network (CCapFPN), which is designed to efficiently and accurately detect road cracks under different conditions. Capsule networks are employed to encapsulate the intrinsic features of cracks, and a feature pyramid architecture is utilized to blend these features in order to enhance the resolution of cracks. A comprehensive comparison of seven algorithms, including CCapFPN and deep fully convolutional network (FCN), on eight datasets, such as PCD19, CFD, and Crack500, demonstrated that this method outperforms existing deep learning methods.

Xu et al. [68]. conducted a comparative analysis of the performance of Faster R-CNN, Mask R-CNN, and YOLOv3. The CRACK500 dataset was employed as the experimental dataset. The experimental results indicate that when the number of images exceeds 130, Faster R-CNN and Mask R-CNN exhibit superior performance compared to YOLOv3. In comparing the performance of Faster R-CNN and Mask R-CNN, it can be observed that Faster R-CNN typically provides more comprehensive bounding boxes.

Feng et al. [15]. proposed a semi-supervised approach for road crack detection using a mobile laser scanning (MLS) system. The method combines a graph convolutional network (GCN) with a graph-widening module, which serves to enhance the image. The method effectively reduces the amount of annotated data required, necessitating only a minimal amount to capture the local features of cracks. The method was trained and tested on a self-built dataset and demonstrated excellent recall and F1 score when compared with five other methods, including U-Net and AU-Net. This semi-supervised learning method reduces the reliance on large annotated datasets for road maintenance tasks.

Liu et al. [69]. proposed segmentation R-CNN, a model that combines pixel-wise and region-wise methods, effectively improves road crack detection. An additional branch for pixel-level segmentation was added using the improved Faster R-CNN framework, which was able to improve the detection of crack features. The performance evaluation was performed on a self-constructed dataset and compared with FCN and Mask R-CNN, and the results show that the method significantly reduces the computational cost and improves the accuracy of crack detection.

Tran et al. [70]. used Mask R-CNN and image processing techniques for road crack detection, which introduced a two-step process approach. The Mask R-CNN was first trained on a self-generated dataset, which was able to classify the cracks more accurately with an accuracy of 92.10%. The width of the cracks was then measured to assess the severity of the cracks. This approach significantly improves the efficiency of the road management system.

Jiang et al. [71]. proposed a two-stage deep learning method, DDSNet, for road crack detection. The first stage is to optimize the YOLOv4 algorithm to identify cracks in complex environments by providing the specific locations of the cracks. In the second stage, the Deeplabv3+ model is used to segment the detected cracks at the pixel level. Comparison with nine existing models, such as SegNet, Unet, PSPNet, etc., provides significant advantages in inference speed and accuracy. Furthermore, the authors provide a scalable solution that adapts to different training data volumes and conditions.

Li et al. [72]. proposed a closed-loop feedback (CLF) approach using generative adversarial networks (GANs) for road crack detection, called CrackCLF. This method is capable of more accurately identifying cracks and the background. The effectiveness of CrackCLF was verified by testing it on three datasets: CFD, Crack500, and Crack700. Compared with methods like U-Net, DeepCrackZou, U-HDN, this method shows excellent performance in precision and recall.

Tabernik et al. [73]. proposed a deep learning model called SegDecNet++. The method combines pixel segmentation and image classification and uses the classification results to improve segmentation accuracy in the training and inference phases. The method trains on a combination of CFD, CRACK500, CrackTree200, DeepCrack, GAPs384, Rissbilder, and non-crack datasets, and achieves a good Dice score of 81% and an IoU of 71%. Ablation experiments showed that the integration of classification information significantly improves the segmentation performance.

Wang et al. [74]. proposed the CrackNet-M method to achieve 3D image-based road crack detection. It incorporates the central branch net (CBN), crack map enhancement (CME), and pooling feature pyramids modules to improve the crack detection capability and detection speed of the method. The model, trained on a self-generated dataset of 2500 3D images and then tested on a test dataset of 200 images, achieves high precision (94.28%), recall (93.89%), and F-measure (94.04%). The model can effectively detect coarse and fine cracks, as well as complex road conditions such as shoulder collapse.

Fan et al. [75]. developed a two-step shadow removal-oriented crack detection (SROCD) method that focuses on removing shadows before finding cracks. This makes the method more stable under different lighting conditions and eliminates the problem of shadows interfering with road crack detection. To better account for shadow interference, a targeted dataset called Shadow-Crack was developed that contains different types of shadows and cracks. After training on this data and testing on the GAPs 384, Cracktree 200, Crack500, CFD, and AEL datasets, it is compared to the FCN, residual complex filter (RCF), holistically nested edge detection (HED), and feature pyramid and hierarchical boosting network (FPHBN) methods. The results show that shadow removal-oriented crack detection SROCD has excellent performance in shadow removal and crack detection.

Khan et al. [76]. present a robotic system based on the depth-based RCDNet for road crack detection. The robotic system, which combines navigation and road crack detection, can be used in both indoor and outdoor environments. An encoder–decoder architecture and advanced modules such as context-embedded channel attention (CECA) and global attention module (GAM) are used by the RCDNet to make crack detection more accurate. Tested on the Crack500 dataset, the accuracy is 96.29%, the cube coefficient is 97.33%, and the IoU is 96.90%. Based on the detected cracks, the system can also create a crack severity map that indicates the areas that need road repair.

Gui et al. [77]. proposed a profile component decomposition model with holistically nested edge detection (PCDM-HED), a framework for 3D road crack detection. It can effectively enhance the crack edge features and improve the accuracy of crack recognition in complex environments. Evaluated on LS-3D, LS-3D, LS-3D, LCMS, ESAR, and 2D-I datasets, it achieves excellent results. PCDM-HED shows great promise for improving the robustness and generalization of road crack detection systems, especially in environments with limited marker data.

Yu et al. [78]. extended the original YOLOv5 network, called YOLOv5-CBoT. The model borrowed the bottleneck transformer and C2f module from YOLOv8, which can effectively improve the accuracy and efficiency of crack identification. The model effectively improves the acquisition of global information and further enriches the gradient information. The model is tested on the RDD2020 dataset and compared with eight other models, including Faster R-CNN, Cascade R-CNN, CenterNet, etc. The experimental results show that YOLOv5-CBoT achieves competitive results with fewer parameters. This makes it a viable solution for efficient and cost-effective road maintenance.

Du et al. [79]. proposed an efficient road crack detection method that can perform object detection and semantic segmentation simultaneously. The method is based on the YOLIv4 model and uses an attentional feature pyramid network (AFPN) to improve the feature extraction capability. A denoising autoencoder (DAE) network is integrated to improve the accuracy of crack segmentation. Tested on the DeepCrack dataset, the performance is similar to that of seven models, including Faster R-CNN, DeepLabv3+, U-Net, etc., while significantly reducing the computational requirements. It has great potential for future practical applications.

Qiu et al. [80]. Qiu et al. integrated deep learning models into a UAV for road crack detection. The authors tested the YOLOv2-tiny, Darknet-19-based YOLOv2, ResNet50-based YOLOv2, YOLOv3, and YOLOv4-tiny models to see how well they could find cracks quickly and accurately. The ResNet50-based YOLOv2 and YOLOv4-tiny emerged as the top performers, with accuracies of 94.54% and 91.74% and processing speeds of 71.71 fps and 108.93 fps, respectively. The system demonstrates the ability to detect road cracks under challenging conditions.

Alshawabkeh et al. [81]. proposed a deep learning model that combines the ResNet-18 model, the whale optimization algorithm (WOA), and the random forest (RF). The model can effectively optimize the feature set and improve the classification performance. The training accuracy on the self-constructed dataset reaches 97.16%. This approach not only improves the efficiency and accuracy of road crack detection but also provides a scalable solution that can be applied to a wider range of road maintenance applications.

### 5.3. Segmentation

Mei et al. [48]. proposed the use of a commercially available sports camera, GoPro, to capture image data. They then constructed a novel method ConnCrack, which incorporates a conditional Wasserstein generative adversarial network (cWGAN) for road crack image detection. The method was pretrained on ImageNet and CFD datasets and compared with methods such as U-Net and VGG19-FCN on the homegrown dataset EdmCrack600, and the results show that ConnCrack has a significant advantage over other methods.

Yang et al. [26]. propose a new algorithm, FPHBN, to address the problem of low contrast between cracks and surrounding images. This algorithm is inspired by the HED framework and effectively detects road cracks. To verify the excellence of this method, the author compared it with four other methods, such as HED, RCF, etc. on five datasets, such as CRACK500, GAPs384, etc. Numerous experiments have shown that FPHBN outperforms the other methods in terms of accuracy.

Huyan et al. [32]. collected road crack datasets using smartphones and digital cameras, but noise from the pavement background and roads affected the quality of these crack images. Conventional methods usually fail to extract accurate crack information from pavement images. This study proposes and optimizes CrackU-Net, a crack detection method using Adam's algorithm. The performance of CrackU-Net is compared with traditional methods, fully convolutional networks (FCNs), and U-Net, and the results show that CrackU-Net outperforms the other detection methods.

Mei et al. [82]. developed the densely connected deep neural network (DNN), an automatic road crack detection method that looks at how pixels are connected and adds a new loss function to fix the problem with the output of the transposed convolutional layer. The authors also compare the method to 11 other algorithms, including FPHBN, U-Net, CrackNet-V, etc., on two datasets, CFD and EdmCrack1000, and our experiments show that the method performs better overall.

Fei et al. [31]. proposed a DNN called CrackNet-V for pavement crack detection, which use the backbone with VGG, and a new activation function called leaky rectified tanh is proposed to improve the crack detection accuracy. Trained and tested on the PaveVision3D dataset, CrackNet-V has better overall performance compared to the CrackNet method, especially in the detection of small cracks.

Wang et al. [83]. proposed an efficient pavement crack segmentation model based on deep learning. The model is based on the pyramid attention network (PAN) and uses DenseNet121 as the encoder. Cross Entropy and Dice are the loss functions. To verify the effectiveness of the method, the author trained and tested it on Crack500, DeepCrack, GAPS384, and MCD datasets, and the experiments proved that the loss function can effectively improve the performance of the model.

Zhang et al. [84]. created an adaptive feature fusion (AFF) module and a segmentation branch module for their proposed pixel-level crack detection network, APLCNet, to detect pavement cracks. The AFF module and the segmentation branch module were created to emphasize the location information of the cracks and to improve the detailed information of the mask prediction. On the CFD dataset, APLCNet achieves a precision of 92.21%, a recall of 94.89%, and an F1 score of 93.53%, demonstrating that the method outperforms CrackForest and MFCD.

Wang et al. [85]. propose a real-time pavement crack segmentation method inspired by Xception and BiSeNet. The model consists of two components: a spatial path and a contextual path. The spatial path uses three convolutional layers to encode sufficient spatial information. The Xception network, which rapidly down-samples the feature map, provides the basis for the spatial data. The feature map serves as the model for the contextual path network. The model is trained and tested on the Crack500 dataset, and the experimental results show that it is comparable to four other methods, such as FC-DenseNet103, DenseASPP, and DeepLabV3+. In comparative tests, the method achieves superior performance in terms of frames per second (FPS).

Tang et al. [86]. proposed an encoder–decoder network (EDNet) that modifies the ResNet-34 architecture as an encoder network, drawing inspiration from CNN-based autoencoders. In this paper, the authors experimented using the PaveVison3D and CFD datasets and compared this method with models such as CrackForest, Cracknet-V, and U-Net, and the results showed that EDNet outperformed the others. The F1 scores on PaveVison3D and CFD were 97.80% and 97.82%, respectively.

Guan et al. [87]. proposed a 3D crack segmentation model that combines the multi-view stereo imaging technique with U-Net to achieve engaged crack and pit segmentation. To complete the experiment, the team's proposed approach uses a 3D pavement model to simultaneously generate color, depth, and overlapping images. Experiments on this dataset show that the model outperforms GCU-Net models in terms of segmentation accuracy and inference speed.

Li et al. [88]. proposed a fully convolutional neural network based on deep supervised networks and dense connectivity for image pixel-level detection. The deep supervision module can effectively improve the performance of the network, the network can extract more features, and the dense connectivity layer can effectively highlight crack features. Finally, we fuse feature maps of different scales to realize the complementarity of different levels. To verify the effectiveness of the different modules in the model, this author designed ablation experiments. The final experiment demonstrates the high accuracy, speed, and robustness of the method.

Polovnikov et al. [89]. The goal of the research was to develop a road crack detection method with high real-time performance. Based on the U-Net network architecture, the DAUNet detection method was developed. To validate the effectiveness of the method, experiments and tests were conducted on five datasets, such as Crack500, GAPs384, and CrackTree200. And it is compared with four mature methods, such as FPHBN. The experimental results show that the method has high superiority in crack detection in complex environments.

Cao et al. [90]. proposed to eliminate the noise of the road image based on a fractional integral-based filtering method while preserving the persistent texture information of the road image, and to use the fractal dimension to detect the shape of the cracks. A network called fractional integral and fractal dimension (FIFD) is designed. Extensive experiments are conducted based on a self-constructed dataset. The experiment compares the threshold, edge, valley and region methods, and the experimental results show that the method outperforms the existing methods in terms of accuracy and generality.

Zhang et al. [91]. developed a weakly supervised learning approach for road crack detection to make road crack detection more cost-effective. The method proposes to compute pseudo-labels using the GrabCut algorithm and proposes a dynamically balanced binary cross-entropy loss function, which is used to solve the imbalance of positive and negative samples. The results show that the method is able to detect road cracks with a high detection rate despite the reduction of manual labeling.

Zhong et al. [92]. introduced a new deep learning framework for road crack detection. This framework, called W-Segnet, has two encoder–decoder models with multi-scale feature fusion and skip connections. The model was trained and tested on four datasets—CFD, CRACK500, CrackTree200, and EdmCrack600—and the results showed that the model performs very well in different scenarios and outperforms existing models such as U-Net, SegNet, and PSPNet.

Golding et al. [10]. proposed the idea that color is not a critical feature for crack detection in deep learning models for image-based road crack detection. To investigate the effect of color on CNN performance, the authors processed 40,000 RGB images using grayscale, thresholding, and edge detection image processing techniques. The experimental results show that the performance of grayscale images is comparable to that of RGB images, indicating that color is not a critical feature for the deep learning model. Thresholding and edge detection show performance degradation. This study highlights that grayscale preprocessing improves the efficiency of crack detection without losing key features.

Wen et al. [93]. proposed a novel deep learning framework called PCDNet that aims to effectively detect pavement cracks using 3D images. PCDNet combines a CNN with an improved pixel-level crack seed algorithm in a three-step process that divides 3D pavement images into patches, finds cracks, and ensures that they remain connected. The author created a dataset of 4300 images to train and test the model. Comparisons with the improved canny and crack seed methods show that PCDNet has high precision, recall, and F1 scores, while this method significantly reduces the time required to train the dataset.

Qu et al. [94]. proposed the DCANet-SE-ResNet method for road crack detection. The model is based on ResNet50 and includes hierarchical feature fusion and an associated attention mechanism. To refine the crack details, the depth separable convolution is combined with the dilated convolution. This approach improves the performance of crack edge representation and the overall segmentation capability. Performance is compared with FPHBN, DeepCrack, U-Net, SegNet, and CrackSegNet on the CFD, Crack500, and DCD datasets. The overall performance is superior to these existing methods. The algorithm has made significant progress in its ability to distinguish cracks from spots and obstructions.

Xu et al. [95]. proposed the enhanced high-resolution semantic network (EHRS-Net) to optimize pixel-level crack detection in pavement evaluation. To enhance image detail, the method combines resolution maintain flow (RMF) and stacked atrous spatial pyramid pooling (SASPP). Performance evaluations on the CFD-ex and HRSD datasets have shown excellent results. In particular, the ability to detect microcracks is leading.

Maurya et al. [96]. proposed to use the feature fusion module in the encoder–decoder architecture to extract detailed crack features, enabling the creation of a global context and pyramidal scale-guided convolutional neural network, primarily for small-target detection. Cross-entropy, Tversky, and Lovász hinge losses resolve the imbalance between cracks and background pixels. Training and testing on four datasets, Crack500, DeepCrack, GAPs384, and MCD, show that the method is not only highly accurate but also fast, providing an excellent solution for road crack detection.

Liu et al. [97]. present a semi-supervised semantic word segmentation method using cross-consistency training (CCT) for efficient road crack detection. This method relies on unlabeled crack samples to ensure consistency between primary and secondary decoder predictions. These predictions examine modified versions of the same encoder output. The method labels only 60% of the data, reducing manual labeling effort. When tested on a self-generated dataset, it outperforms methods such as U-Net, SegNet, and Deeplabv3+.

Zhang et al. [98]. introduced an efficient crack segmentation neural network (ECSNet) for real-time road crack detection. The network integrates small kernel convolutional layers, parallel max-pooling, and convolutional operations, which can effectively reduce model parameters and improve computational efficiency. Tests are performed on the DeepCrack dataset, and performance comparisons are made with DeepLabV3, FCN, LRASPP, Enet, Unet, and DeepCrack. The results show that DeepCrack completes training in the shortest time and achieves the second highest accuracy. The high computational speed and leading accuracy make this method an effective solution for practical applications requiring rapid pavement condition assessment.

In Guo et al. [99], to make pixel-level crack detection more accurate, an UperNet with an attention module acts as a decoder, and a transformer-based semantic segmentation network acts as an encoder, effectively improving the crack feature acquisition capability. After comparative tests with ANN, FCN, PSPNet, UNet and STU models on three datasets—CFD, Crack 500, and CrackSC—the proposed model shows the highest performance in terms of F1 score and recall. The network demonstrates superior detection of fine and complex pavement cracks under noisy conditions.

Lin et al. [100]. proposed using the PSA-Net deep learning architecture for road crack detection. The network effectively integrates spatial and contextual information by using a feature pyramid and an attention mechanism. This enables accurate detection in complex road environments. Tested on a self-constructed dataset and compared with five methods such as HED, RCF, PCN, etc., the results show that PSA-Net is superior to existing methods.

Qu et al. [101]., based on the SegNet model, combine a densely connected architecture with a gating attention mechanism, while adding an atrous convolutional dense connection module (AD-block), which enables the algorithm to effectively recognize different crack features. A gating attention unit (GAU) is introduced to improve the accuracy of crack localization. Tested on the DeepCrack, CFD, and Crack500 datasets, the proposed method achieves an MIoU of 87.53%, a precision of 87.67%, a recall of 85.41%, and an F1 score of 86.52% on the DeepCrack dataset. The results show that the method provides an effective solution for road crack identification.

Table 16 shows all the publicly available datasets mentioned above, with links to download each one.

**Table 16.** List of the public datasets along with access links, all accessed on 3 May 2024.

| Dataset | Links |
|---|---|
| AEL | https://github.com/Jiawei-Yao0812/AerialLaneNet (accessed on 3 May 2024) |
| CCIC | https://data.mendeley.com/datasets/5y9wdsg2zt/2 (accessed on 3 May 2024) |
| CFD | https://github.com/cuilimeng/CrackForest-dataset (accessed on 3 May 2024) |
| CRACK500 | https://github.com/fyangneil/pavement-crack-detection (accessed on 3 May 2024) |
| CrackLS315 | https://github.com/qinnzou/DeepCrack (accessed on 3 May 2024) |
| CrackTree200 | https://github.com/fyangneil/pavement-crack-detection (accessed on 3 May 2024) |
| CrackTree260 | https://github.com/qinnzou/DeepCrack (accessed on 3 May 2024) |
| CRKWH100 | https://github.com/qinnzou/DeepCrack (accessed onv) |
| DeepCrack | https://github.com/yhlleo/DeepCrack (accessed on 3 May 2024) |
| EdmCrack600 | https://github.com/mqp2259/EdmCrack600 (accessed on 3 May 2024) |
| GAPs384 | https://github.com/fyangneil/pavement-crack-detection (accessed on 3 May 2024) |
| RDD | https://github.com/sekilab/RoadDamageDetector (accessed on 3 May 2024) |
| ImageNet | https://www.image-net.org/ (accessed on 3 May 2024) |
| LTPP | https://infopave.fhwa.dot.gov/Data/DataSelection (accessed on 3 May 2024) |
| PaveVision 3D | http://www.pvision3d.com/ (accessed on 3 May 2024) |
| Stone331 | https://github.com/qinnzou/DeepCrack (accessed on 3 May 2024) |

Table 17 shows the links to the codes of the 305 papers screened for bibliometric analysis where the algorithm is publicly available.

**Table 17.** List of algorithms with disclosed codes, all accessed on 25 May 2024.

| Ref | Year | Title | Code Link |
|---|---|---|---|
| [102] | 2019 | Fully convolutional networks for automatic pavement crack segmentation | https://github.com/RyM-CIC/Crack-segmentation (accessed on 25 May 2024) |
| [103] | 2020 | Pavement crack detection using progressive curvilinear structure anisotropy filtering and adaptive graph-cuts | https://github.com/DrEdwardLee/PCmPA-PCmFFA (accessed on 25 May 2024) |
| [104] | 2020 | Token based crack detection | https://github.com/Fan-Meng/CrackTokenToolbox (accessed on 25 May 2024) |
| [26] | 2020 | Feature pyramid and hierarchical boosting network for pavement crack detection | https://github.com/fyangneil/pavement-crack-detection (accessed on 25 May 2024) |
| [89] | 2021 | DAUNet: deep augmented neural network for pavement crack segmentation | https://github.com/dvalex/daunet (accessed on 25 May 2024) |
| [105] | 2021 | Attention-based convolutional neural network for pavement crack detection | https://github.com/wanhaifengytu/CrackSegmentationProject/ (accessed on 25 May 2024) |
| [106] | 2022 | A novel approach for detection of pavement crack and sealed crack using image processing and salp swarm algorithm optimized machine learning | https://github.com/NDHoangDTU/CV_SSA_SVM_Crack_SealedCrack (accessed on 25 May 2024) |
| [65] | 2022 | An efficient method for detecting asphalt pavement cracks and sealed cracks based on a deep data-driven model | https://github.com/CHDyshli/PavementCrackDetection (accessed on 25 May 2024) |
| [107] | 2023 | Multiscale attention networks for pavement defect detection | https://github.com/xtu502/pavement-defects (accessed on 25 May 2024) |
| [108] | 2023 | Computer vision-based recognition of pavement crack patterns using light gradient boosting machine, deep neural network, and convolutional neural network | https://github.com/NhatDucHoang/LightGBM_PaveCrackPatterns (accessed on 25 May 2024) |
| [76] | 2023 | Development of ai- and robotics-assisted automated pavement-crack-evaluation system | https://github.com/Masrur02/AMSEL_robot (accessed on 25 May 2024) |
| [73] | 2023 | Automated detection and segmentation of cracks in concrete surfaces using joined segmentation and classification deep neural network | https://github.com/vicoslab/segdec-net-plusplus-conbuildmat2023 (accessed on 25 May 2024) |

## 6. Findings and Future Research Scope

### 6.1. Findings of the Study

The authors conducted a bibliometric and critical analysis of papers related to image-based road crack detection research. The bibliometric analysis identified trends in the field, influential papers, journals, authors, countries, and keywords. The results of the bibliometric analysis are presented below.

(a) From 2013 to 2015, the number of paper publications was very low, with fewer than five papers per year; from 2016, the number of papers per year began to increase rapidly, fluctuating between 10 and 20 from 2016 to 2019; after 2020, the number of papers published increased dramatically, with the number of papers jumping to between 40 and 50 per year; and after 2022, the number of paper publications per year reached between 70 and 80 papers per year. The number of papers published from 2020 to 2023 represents about 58.52% of the total number of papers published at that time.

(b) Refs. [14,26–28] are the most influential papers in the field of image-based road crack detection.

(c) *IEEE Transactions on Intelligent Transportation Systems*, *Computer-Aided Civil and Infrastructure Engineering*, *Automation in Construction*, *Construction and Building Materials*, and *Journal of Computing in Civil Engineering* are the most cited journals in the field.

(d) Huyan Ju, Li Wei, Wang Kelvin C.P., Gu Xingyu, Li Gang, Chen Cheng, Zhang Allen, Fei Yue, Li Joshua Q. are influential authors in this field of research.

(e) Countries with greater influence include China, the United States, Canada and the United Kingdom.
(f) The important keywords are deep learning, crack detection, pavement crack detection, damage detection, convolutional neural network, image processing, feature extraction, recognition, system, and semantic segmentation.

In the critical analysis section, the authors categorized the papers into different categories based on the techniques they used and provided an overview of the papers. The results of the critical analysis are listed below.

(a) The deep learning techniques used for crack detection are divided into three categories: classification, detection, and segmentation. Among these, there are relatively few research on the classification technique.
(b) CNN, YOLO, and U-Net are the most commonly used deep learning methods for performing classification, detection and segmentation tasks, respectively.
(c) ResNet is the most commonly used backbone of deep learning methods.
(d) Most methods perform deep learning tasks on the Tensorflow and PyTorch frameworks.
(e) LabelImg is the most widely used annotation tool.
(f) Most researchers use SGD and Adam optimizers to optimize deep learning models.
(g) Using specialized architectures like FPN, FCN, etc., using attention machines like SENet, CoordAtt, and GAU, using a combination of multiple imaging modalities (IR, VIS, 3D), and preprocessing can improve the accuracy of crack detection.
(h) Integrating attention modules (e.g., SENet, CBAM) or feature pyramid networks, can also improve the performance of deep learning methods for road crack detection.
(i) Using architectures such as DenseNet, ResNet, and MobileNet and reduced model size can speed up computation without compromising detection accuracy.

### *6.2. Future Research Direction*

The previous section lists the results of the current study. In addition to the findings, the author identified a range of directions for future researchers by analyzing the screened deep learning-based papers.

(a) Improve the efficiency of data annotation: Create unsupervised learning techniques that reduce the need for manual annotation. Generate diverse datasets that include unusual pavement features, such as hairline cracks and scratches, to improve the reliability of detection systems.
(b) Optimized model structures: To improve the performance of the architectures, incorporate purpose-specific functional modules and multi-scale features to achieve higher levels of accuracy. while simultaneously considering the demands of lightweight and mobile deployment.
(c) Enhanced feature extraction: Improve shadow removal and segmentation accuracy. And increase detection speed, explore attention mechanisms, and explore different model compression approaches.
(d) Quantification and indexing: Use crack quantification techniques to measure crack length, width, and depth, which can help generate numerical pavement condition indices such as the Pavement Condition Index (PCI).
(e) Multi-sensor fusion: Integrate multiple vision sensors for more efficient area coverage.
(f) Better automation: To make detection models more automated, combine classification and segmentation modules to make the most of additional data on edge features and break severity.

## 7. Discussion and Conclusions

This paper presents a comprehensive review of state-of-the-art image-based road crack detection techniques through bibliometric analysis and critical analysis. The bibliometric analysis shows the rapid development of the field, with significant contributions from influential authors, journals, and countries. Deep learning techniques such as CNN, YOLO, and U-Net have made great strides in tasks such as segmentation, classification, and attention. Attention mechanisms, feature pyramid networks, and specialized imaging modalities have also been shown to be very important in improving detection accuracy. Future research should focus on improving the efficiency of data annotation, optimizing model architectures, and integrating multi-sensor fusion. This review can help researchers identify emerging trends, research gaps, and benchmark datasets to start their work. Further exploration of deep learning-based segmentation methods and practical deployment strategies can significantly improve the accuracy and efficiency of crack detection, providing important insights for academia and industry to develop reliable automated road maintenance solutions.

**Author Contributions:** Conceptualization, L.F., S.T., M.K.A.b.M.A., M.I.S.b.I. and R.Z.; methodology, L.F.; software, L.F.; validation, S.T., M.K.A.b.M.A. and M.I.S.b.I.; formal analysis, L.F. and R.Z.; investigation, L.F.; resources, L.F., S.T., M.K.A.b.M.A. and M.I.S.b.I.; data curation, L.F. and R.Z.; writing—original draft preparation, L.F.; writing—review and editing, R.Z.; visualization, L.F.; supervision, S.T., M.K.A.b.M.A. and M.I.S.b.I.; project administration, S.T.; funding acquisition, L.F. and S.T. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Data is contained within the article.

**Acknowledgments:** The work described in this paper was undertaken at the Faculty of Engineering, Universiti Putra Malaysia, Selangor 43400, Malaysia, when L.F. was a PhD student at Universiti Putra Malaysia.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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