

YOLO Algorithm-Based Crack Detection: A Scientometrics Literature Review

Luxin Fan^{1*}, SaiHong Tang^{1*}, Ariffin M.¹, Ismail MIS¹, Xinming Wang¹

¹ Faculty of Engineering, Universiti Putra Malaysia, Serdang, 43400, Malaysia

* Corresponding Author: gs59924@student.upm.edu.my ; saihong@upm.edu.my

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Abstract: *This review paper examines the development and current status of the crack detection research field through bibliometrics and critical analysis, focusing on the You Only Look Once (YOLO) algorithm. The authors evaluate trends in the field, influential research journal articles, and collaborations between different countries from various sources, and conclude that China is at the forefront. The analysis shows a significant increase in the number of publications since 2019, highlighting the growing interest of researchers in automated crack detection. A critical analysis of key research reveals the improvement of YOLO algorithms to address challenges such as changing lighting and complex backgrounds, highlighting the development and application of YOLO in infrastructure maintenance to improve accuracy and efficiency in real-world scenarios.*

Keywords: Crack Detection; Deep Learning; Scientometric Analysis

1. Introduction

The maintenance of civil infrastructure is critical to safety and economic efficiency and increasingly relies on automated systems to identify structural damage, such as cracks. Traditional manual inspections, while widely used, are labor-intensive and prone to human error, highlighting the need for more accurate and automated methods. The authors divide crack detection into three steps: first we acquire the crack image, then we pre-process the acquired image, and finally we classify, detect, and segment the processed image. The YOLO algorithm in the field of detecting and classifying different types of cracks plays a crucial role. This study aims to perform bibliometric and critical analyses to examine the development history and the current state of research in this field. In addition, This will be done to identify research trends, influential journal articles, journals, authors and countries in the field, and to explore the research opportunities in the field. The mode of collaboration in this research field will be explored.

2. Research Methodology

This study combines bibliometric and critical analyses to provide a systematic analysis of journal articles on YOLO crack detection algorithms. Figure 1 describes the general methodology in the research:

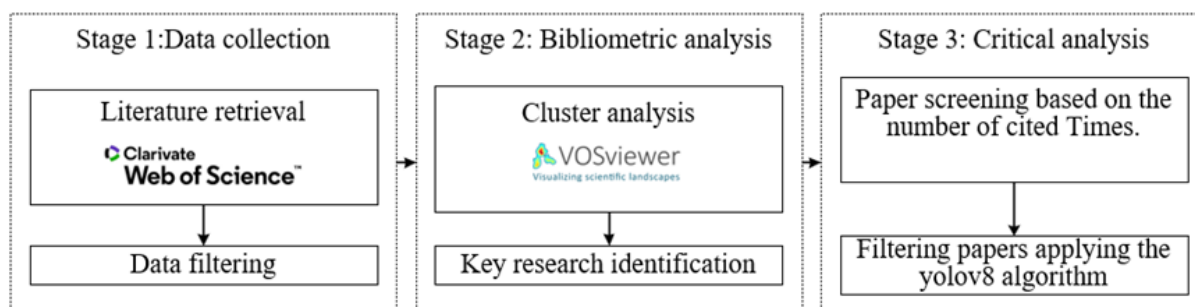


Figure 1: Summary of Research Methodology

The first stage involved the collection of primary journal articles data for this review article. Next stage involves bibliometric analysis to identify key research fields. The third stage involves the specific analysis of the journal articles based on their abstracts, methods and results, and a short summary of the evolution of crack detection algorithms based on the YOLO framework.

In order to conduct a comprehensive literature review, the authors followed a predetermined set of criteria to select the most relevant journal articles. Figure 2 depicts the literature search and data screening process (referred to as stage 1 in Figure 1). Based on the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) approach, which stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses, the data collection process consisted of four distinct phases: identification, screening, eligibility, and inclusion (Liberati, 2009).

Phase 1: In May 2024, the authors search for journal articles on the Web of Science article search page. The authors limit the search string to the 2015 to present timeframe using the search term "YOLO". The authors select only document types for articles to ensure the originality of the journal articles. At the end of Phase 1, the authors identified a total of 4143 journal articles.

Phase 2: From the 4143 journal articles screened, journal articles were relevant to crack detection scenarios were considered, based on their title and abstract. In this phase, a grand total of 4034 journal articles were eliminated.

Phase 3: Conducted a full-text search to evaluate the remaining 109 journal articles. If a journal article (a) focuses its research not on the YOLO algorithm, but on the application of the YOLO algorithm to comparative testing, and (b) does not innovatively and effectively contribute to the field of crack detection research based on the YOLO algorithm, it was excluded from the journal articles. In total, 15 journal articles were excluded. Therefore, the number of extracted journal articles was 94.

Phase 4: Upon completion of all previous phases, this work included 94 journal articles in this review for bibliometric analysis. And selected the 10 most influential journal articles and 5 newly published journal articles for critical analysis.

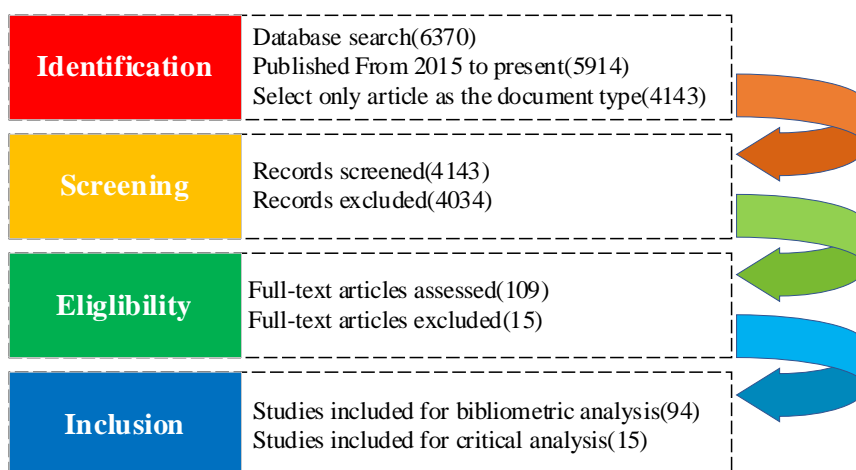


Figure 2: Summary of the procedure for retrieving and filtering literature

3. Bibliometric Analysis

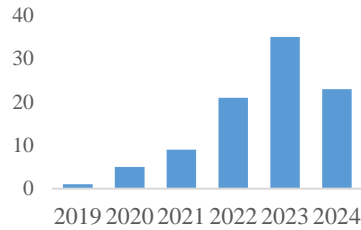
Bibliometric analysis evaluates the scholarly merit of journal articles, publishers, and authors, identifies research trends in a given research topic by using statistical techniques such as the number of publications, frequency of cited, and collaboration patterns. The authors conduct a bibliometric analysis of the journal articles in the screened database using the data visualization tool VOSviewer(Cha et al., 2017), Next, the authors investigate the most influential authors, publishers, countries, and journal articles in crack detection research based on the YOLO algorithm and demonstrate the scientific mapping analysis. The scientific mapping analysis includes co-authorship, co-citation, and keyword occurrences. The co-citation analysis identifies links between different journal articles. The co-authorship analysis identifies patterns of collaboration between countries and institutions. By looking at the number of keyword occurrences, it is possible to understand research trends and important terms in the field.

3.1 Overview of the Publications.

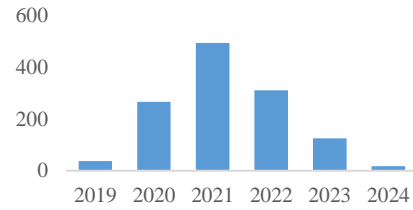
3.1.1 Annual Analysis of the Publications.

The authors screened articles from the Web of Science journal article repository from 2015 to the present (May 11, 2024) and analyzed a total of 94 journal articles for bibliometric analysis. Figure 3a displays the annual count of publications. The figure shows that no researchers have applied the YOLO algorithm to crack detection research since its inception in 2015. The first journal article applying the YOLO algorithm to crack detection research appeared in 2019, and since then, the number of related journal articles has grown rapidly, with the number of journal articles per year almost doubling. It reached 35 journal articles in 2023. The number of journal articles published in the first five months of 2024 alone reached 23, surpassing the 21 journal articles published in the whole of 2022. This clearly signifies that many researchers will be devoting more effort to the field of crack identification based on YOLO.

The authors also analyzed the number of citations for journal articles published each year. Figure 3b shows the distribution of citations per year for the publications. The figure shows a normal distribution of citations for each year of publication, with 2021 having the highest number of citations. The authors concluded that the gradual decrease in citations for journal articles from 2022 to the present does not indicate a gradual stagnation of research in the field, but rather a lower number of citations due to the later and shorter publication dates of these journal articles.



(a) Number of publications



(b) Number of received citations

Figure 3: Summary of annual characteristics of the publications

3.1.2 The Most Cited Publications.

In this subsection, the authors analyze the most impactful journal articles among the 94 journal articles screened. The authors establish a minimum requirement of 37 citations to extract 10 journal articles. The 10 journal articles cited 769 times, which is approximately 61.27% of the total citations for all journal articles. This shows that these 10 journal articles play an important role in crack detection based on the YOLO algorithm. Table 1 summarizes the most cited journal articles by author, reference, journal, country, citation, and average citation. The journal articles are sorted in descending order by their citations. The International Journal of Pavement Engineering published the journal article "Pavement distress detection and classification based on the YOLO network" in 2021, with 174 citations, ranking it first. This journal article has a very high impact, there are 58.00 citations per year on average.

Table 1: Overview of the most frequently referenced journal articles

Ref.	Title	Journal	Country	Citation	Average Citation
(Du et al., 2021)	Pavement distress detection and classification based on YOLO network	International Journal of Pavement Engineering	China	174	58.00
(Majidifard et al., 2020)	Deep machine learning approach to develop a new asphalt pavement condition index	Construction And Building Materials	USA	123	30.75
(Li et al., 2021)	Detection of concealed cracks from ground penetrating radar images based on deep learning algorithm	Construction And Building Materials	China	116	38.67
(Park et al., 2020)	Concrete crack detection and quantification using deep learning and structured light	Construction And Building Materials	South Korea	97	24.25
(Jiang et al., 2021)	A deep learning approach for fast detection and classification of concrete damage	Automation In Construction	China	56	18.67
(Tan et al., 2021)	Automatic detection of sewer defects based on improved you only look once algorithm	Automation In Construction	China	45	15.00
(Ma et al., 2022)	Automatic Detection and Counting System for Pavement Cracks Based on PCGAN and YOLO-MF	IEEE Transactions on Intelligent Transportation Systems	China	43	21.50
(Wu et al., 2022)	Autonomous surface crack identification of concrete structures based on an improved one-stage object detection algorithm	Engineering Structures	China	39	19.50

(Teng et al., 2021)	Concrete Crack Detection Based on Well-Known Feature Extractor Model and the YOLO_v2 Network	Applied Sciences-Basel	China	39	13.00
(Zhang et al., 2022)	Automated bridge surface crack detection and segmentation using computer vision-based deep learning model	Engineering Applications of Artificial Intelligence	China	37	18.50

3.2 Influential Journals, Authors, and Countries.

3.2.1 The Most Productive Journals.

In this subsection, the authors have listed the journals that have made outstanding contributions to the field of crack detection based on the YOLO algorithm. 58 different journals published the collected 94 journal articles. The authors extracted the top 6 publication sources based on the number of journal articles published. These 6 journals published a total of 37 (39.36%) of the 94 journal articles. The remaining 52 journals contained 57 (60.64%) journal articles. Table 2 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 table is sorted by the number of journal articles published. Table 2 shows that the journal "Applied Sciences-Basel" publishes 10 journal articles but receives only 56 citations. The journal "Construction and Building Materials" has only five journal articles, but the number of citations is as high as 339. The journal "Automation in Construction" has 7 journal articles with a total of 185 citations, which has the highest H-index, indicating that the journal articles in this journal have a high overall level.

Table 2: Summary of the most efficient academic journals

Journal Name	Total Publications	Total Citations	Average Citations	Impact Factor	5 Years Impact Factor	Publisher	H-Index
Applied Sciences-Basel	10	56	3.00	2.29	5.6	MDPI	3
Automation In Construction	7	185	13.05	16.75	26.43	Elsevier B.V.	6
Sensors	7	81	5.29	7.50	11.57	MDPI	5
Construction and Building Materials	5	339	19.33	-	67.80	Elsevier Sci Ltd	3
IEEE Access	4	23	1.92	0	5.75	Institute of Electrical and Electronics	1
International Journal of Pavement Engineering	4	181	16.25	3.50	45.25	Taylor and Francis Ltd.	3

'-' indicates that this data is not available.

3.2.2 The Most Productive Authors.

This subsection discusses the most prolific authors in the field of crack detection based on the YOLO algorithm. The screened Web of Science dataset collected 94 journal articles from 410 authors. The authors created Table 3 displays the top 5 authors ranked by the number of publications they have produced. It summarizes the most prolific authors by author name, total publications, total citations, average citations, first author, H-index, and country. According to the summary table, Teng Shuai is the author with the highest number of publications, having published four journal articles. The other four authors in the top five have published three journal articles. Dong Qiao, the second-ranked author among these five, published one journal article that received 123 citations, making the author with the most citations. This work also investigated whether there are authors with a small number of published journal articles but a

high number of citations, and the results show that although Du Yuchuan's has only published one journal article, the quantity of citations for this journal article is as high as 174, which fully demonstrates that this author has a high influence in the field of YOLO-based crack detection.

Table 3: Summary of the most productive authors

Author's Name	Total Publications	Total Citations	Average Citations	As 1st Author	H-Index	Country
Teng Shuai	4	65	6.88	2	3	China
Dong Qiao	3	123	15.22	0	2	China
Chen Gongfa	3	49	6.50	0	3	China
Qian Songrong	3	47	9.5	0	3	China
Zhang Tian	3	9	11.17	0	3	China

3.2.3 The Most Productive Countries.

In this subsection, the authors examine the most influential countries in crack detection research based on the YOLO algorithm. In the screened Web of Science dataset, 94 journal articles from 20 countries were filtered. Figure 4 shows the distribution of these 94 journal articles across the 20 countries. Larger circles in this figure indicate that more journal articles were published in that particular country.

Table 4 shows the total publications, total citations, average citations, number of cited journal articles greater than or equal to 100/50/30/10, and H-index of the top three countries according to the number of publications of each country, and it can be seen that China's total publications are as high as 71, and the journal articles of the rest of the countries do not even exceed 10, which shows that China has an irreplaceable position in this field. Although the total number of journal articles in the second-ranked United States is only 8, there is still 1 journal article with more than 100 citations and a total of nine journal articles with more than 10 citations, which shows that the United States has an important influence in this field.



Figure 4: Geographical distribution of the publications

Table 4: Summary of the most productive countries

Country	TP	TC	AC	≥100	≥50	≥30	≥10	H-Index
China	71	913	7.87	2	1	7	9	15
United States	8	208	6.33	1	0	1	5	9
India	5	36	4.33	0	0	1	1	4

TP (total publications), TC (total citations), AC (average citations).

3.3 Science Mapping Analysis.

3.3.1 Co-Citation Analysis.

The author considered co-citation analysis to be one of the science mapping techniques. Journal article C cites both journal articles A and B, resulting in a co-citation. The author performs a co-citation analysis on the cited source. When two sources or two authors are cited at the same time, it means that they have the same research field and interest.

First, the co-citation network of cited sources is analyzed. In this subsection, the authors searched 1291 source journals for the references of the 94 reviewed journal articles and filtered the top 10 sources in terms of total link strength for analysis. Link Strength indicates the number of times a journal article from a particular two journals has been cited by a journal article at the same time. Figure 5 uses the VOSviewer software to show the relationship between these 10 source journals. Each nodal circle represents a journal; the larger the circle, the larger the citations, and the connecting line between each two circles represents the link strength between these two journals. The link strength increases with the thickness of the line.

As can be seen in Figure 5, the journals are grouped into two clusters, red and green, with journals in each cluster indicating a stronger link between them. The two most prominent journals in the red cluster are "Automation in Construction" and "Computer-Aided Civil and Infrastructure Engineering", the research on crack detection based on the YOLO algorithm clearly shows a strong correlation with these two journals. The two most prominent journals in the green cluster are "Proceeding CVPR IEEE" and "arXiv", with total link strengths of 3543 and 2890, respectively, which are among the highest among all journals in the green cluster. Indicating that these two journals have an important influence on the research field of YOLO algorithm for crack detection.

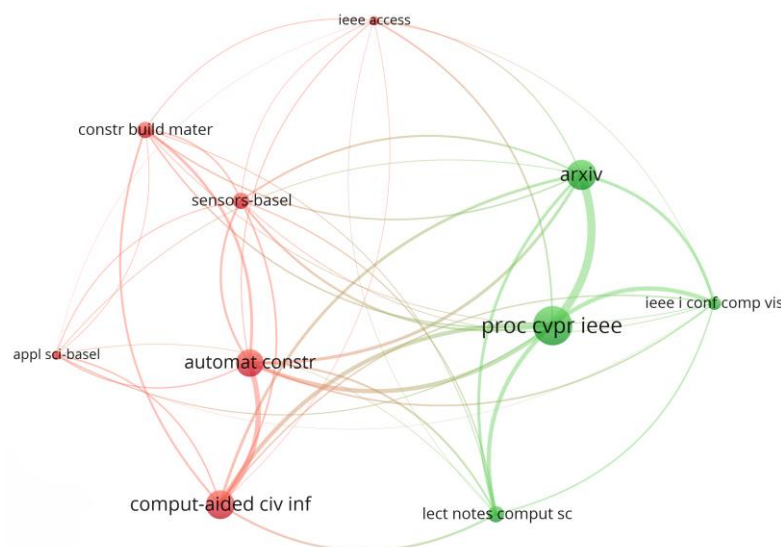


Figure 5: Co-citation analysis of the sources

Table 5: Co-citation indices of the sources

Source	Citations	Total Link Strength
Proceeding CVPR IEEE (proc cvpr ieee)	258	3543
arXiv (arxiv)	200	2890
Automation in Construction (automat constr)	182	2645
Computer-Aided Civil and Infrastructure Engineering (comput-aided civ inf)	189	2446
Lecture Notes in Computer Science (lect notes comput sc)	111	1834
IEEE Conference on Computer Vision and Pattern Recognition (ieee i conf comp vis)	87	1637
Sensors (sensors-basel)	110	1533
Construction and Building Materials (constr build mater)	109	1469
Applied Sciences (appl sci-basel)	62	897
IEEE Access (ieee access)	63	860

Next, the co-citation network of the cited authors is analyzed, and from the 2312 cited authors, the ten authors with the highest number of co-citations, i.e. the top ten authors in terms of total link strength, as shown in Table 6. Figure 6 shows the relationship between these ten authors. The figure also divides these ten authors into two clusters. Interestingly, the red cluster has the absolute advantage, and the authors' citation counts and link strengths are much higher than those of the two authors in the green cluster. One of the authors, Joseph Redmon, stands out the most, with 93 citations and a total link strength of 460, far exceeding the figures for the other nine authors. This indicates that Joseph Redmon has a key position in the field of YOLO-based crack detection.

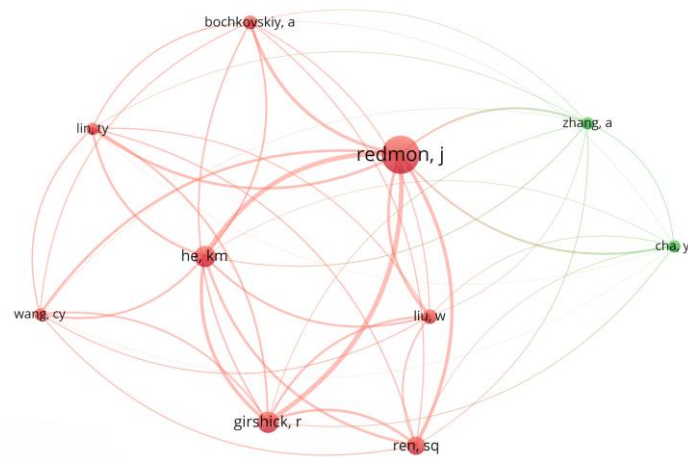


Figure 6: Co-citation analysis of the cited authors

Table 6: Co-citation indices of the cited authors

Author	Citations	Total Link Strength
Joseph Redmon (redmon, j)	93	460
Kaiming He (he, km)	52	341
Ross Girshick (girshick, r)	52	333
Shaoqing Ren (ren, sq)	45	263
Wei Liu (liu, w)	36	230
Tsung-Yi Lin (lin, ty)	31	223
Alexey Bochkovskiy (bochkovskiy, a)	35	215
Chien-Yao Wang (wang, cy)	30	202
Allen Zhang (zhang, a)	31	132
Young-Jin Cha (cha, yj)	31	111

3.3.2 Co-Authorship Analysis.

In this subsection, co-authorship analysis is performed on the 94 selected journal articles by country to examine the cooperation between authors from different countries. Table 7 lists the top six countries in terms of total link strength. Figure 7 shows the collaboration situation between these six countries. In Table 7, each node represents the number of journal articles published in the country, with larger nodes indicating more publications. A line between two nodes indicates that there is a cooperative relationship between the two countries. The figure 7 clearly shows that China, the United States, and the United Kingdom have mutually beneficial cooperative relationships. Japan only has a cooperative relationship with China. India and South Korea have no cooperative relationships with other countries.

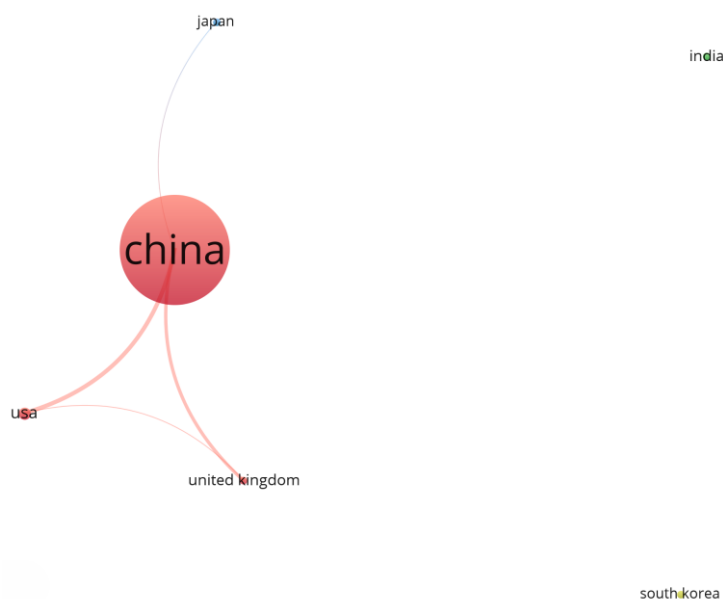


Figure 7: Visualizing the co-authorship network between countries

Table 7: Co-authorship indices of the countries

Country	Documents	Total Link Strength
China	71	10
USA	8	6
United Kingdom	4	5
Japan	3	1
South Korea	3	0
India	5	0

3.3.3 Co-Occurrence Analysis.

An analysis of keywords co-occurrence was conducted to examine research trends and hotspots in the field of crack detection using the YOLO methods. The screening of 94 journal articles yielded a total of 407 keywords, 14 of which had more than 4 occurrences. Table 8 ranks these 14 keywords according to the number of occurrences.

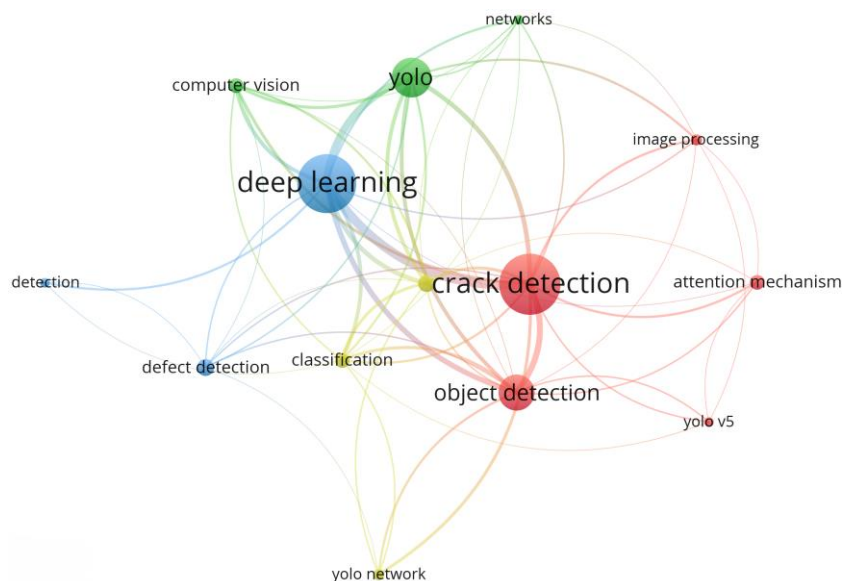


Figure 8: Network visualization of co-occurrences of the keywords

Table 8: Keywords summary

keyword	occurrences	total link strength
Crack Detection	32	53
Deep Learning	31	56
YOLO	21	40
Object Detection	19	38
Damage Detection	9	29
Defect Detection	9	12
Attention Mechanism	8	9
Classification	8	26
Computer Vision	8	21
Image Processing	6	12
Yolo Network	6	12
Detection	5	5
Networks	5	12
Yolo V5	5	7

Figure 8 illustrates the links between different keywords. The figure shows that "deep learning" is the only keyword that is associated with all other keywords, with a total link strength of 56. This shows the importance of deep learning in the field. The authors also found that YOLO v5 is the only specific algorithm that appears in the graph, showing that YOLO v5 is the most popular generation of YOLO algorithms. The figure also shows that optimizing the YOLO algorithm often involves adding or modifying the attention mechanism.

4. Critical Analysis

The authors filter out the 10 most cited journal articles in Section 3.1.2 and then perform a critical analysis of these 10 journal articles. The 10 journal articles are comprehensively analyzed according to the order of the year of publication to further discover knowledge about the YOLO algorithm.

Majidifard et al.(2020) solved the problem of road crack detection, which depends on manual

labor and is expensive, inefficient, and unsafe. Create a dataset for training and testing was generated using 7237 Google Street View images. A hybrid algorithm integrating U-net and YOLO v2 is proposed to quantify and classify road cracks. The overall precision of the experimental data is 93%, the recall is 77%, and the F1-score is 84%. The results show that the model is characterized by high stability, a wide range of applications, and good economic benefits. The author suggests the use of 3D images for further research.

Park et al.(2020) presented a combination of the YOLOv3-tiny algorithm and laser technology is proposed To identify surface fractures in concrete constructions. The dimensions of the cracks are calculated based on the position of the laser projected on the concrete surface, and the laser alignment correction algorithm using a distance sensor is used to improve the accuracy of the measurements. Training and testing were performed on 330,000 images with 94% accuracy and 98% precision. The findings indicate that the method can detect and quantify cracks on concrete surfaces in real time with high accuracy. The method demonstrates that the combination of structured light and distance sensors has a smaller error.

Du et al.(2021) suggested that there is an absence of a consolidated dataset in the field of road crack detection, a total of 45,788 photos were acquired using a camera with high resolution affixed to a vehicle and annotated using the labelImg software, and the dataset was named the PD dataset. The YOLO v3 algorithm received training and underwent testing using this dataset, focusing on the seven different types of cracks. The combined detection accuracy was 73.64%. Strong light or shadows make crack detection difficult, and future work should explore more convolutional layer structures in deep networks, in order to enhance the precision of road crack detecting under these conditions.

Jiang et al.(2021) suggested that there may be loss of function and safety damage to concrete surfaces due to temperature, overloading, corrosion, and inadequate maintenance. The mathematical models of existing automatic detection methods are too complex. The authors optimized the YOLO v3 algorithm using an inverse residual network, depth-separable convolution, and a linear bottleneck structure known as the Fast YOLO algorithm. The authors created the training and test datasets by collecting 5000 concrete images, that containing different types of fractures. The test findings indicate that the enhanced method has an inference speed that is 24.1% and 53.5% higher than the original YOLO v3 and SSD (Single Shot MultiBox Detector) algorithms, respectively. The accuracy of detecting network completeness is 64.81% and 64.12%, showing improvements of 3.25% and 4.04% correspondingly. However, the algorithm is unable to effectively detect concrete surface breakage in images with a complex background.

For the purpose of detecting cracks inside asphalt and concrete roads, Li et al.(2021) proposed a combination of 3D ground-penetrating radar and the YOLO algorithm, divided into two parts: signal processing and image recognition. In the first step, ground penetrating radar was used to collect information about the crack features inside the road, followed by the recognition of simulated images of hidden cracks. The author trained and recognized a dataset of 1306 cracks and 303 GPR (Ground-penetrating radar) images using the YOLO v3, YOLO v4, and YOLO v5 algorithms. The results show that the YOLO v4 algorithm provides a better balance of detection speed and accuracy, and YOLO v5 has the highest accuracy.

Tan et al.(2021) proposed that the sewer system as a civil infrastructure is crucial for the normal operation of a city, but the sewer pipes gradually show defects such as cracks over time. Traditional inspection techniques have limitations in terms of feature extraction and detection

accuracy. The author proposes improvements to the YOLOv3 algorithm, mainly in the areas of data augmentation, loss function, network structure and bounding box prediction. The self-constructed dataset achieves 92% mAP, outperforming the YOLOv3 and faster R-CNN (Region-based Convolutional Neural Network) algorithms.

Teng et al.(2021) in order to evaluate the safety of concrete structures, crack detection based on YOLO v2 is proposed. To improve the detection performance of the YOLO v2 algorithm, 11 feature extractors were tested for comparison. The authors conducted comparative tests of the YOLO v2 algorithm using different feature extractors on a self-constructed dataset of 990 images. The 11 feature extractors include AlexNet, GoogleNet, MobileNetV2, InceptionV3, SqueezeNet, ResNet (18, 50, 101), VGG (16, 19), and InceptionResNetV2. The experimental results show that the Resnet18 model is superior in terms of both accuracy and computational efficiency, with an AP value of 0.89.

Ma et al.(2022) proposed a road crack detection system consisting of the PCGAN (Pavement Crack Generative Adversarial Network) and YOLO-MF. The PCGAN can produce a substantial quantity of images depicting cracks., thus solving the problem of insufficient data set. The authors have added a median flow algorithm to the YOLO v3 algorithm, which effectively detects cracks and counts their number. The accuracy of this algorithm reaches 98.47%, with an F1 value of 0.958. The system can be applied in three ways: handheld inspection, vehicle-mounted inspection, and drone inspection. Future work will focus on extending the model to detect more types of cracks and making targeted improvements for fine cracks and complex road failure problems.

Wu et al.(2022) propose an improved YOLO v4 algorithm that uses the EvoNorm-S0 structure and a pruning technique to improve performance and efficiency in accurately detecting natural deterioration and cracking in concrete structures. The EvoNorm-S0 structure can efficiently find the cracks in complex images, improving the accuracy of crack detection. Pruning is a technique used to reduce the complexity of a network in order to enhance the accuracy of detection. The improved network is compared with SSD300, YOLO v3, YOLO v4, and other algorithms in a self-made dataset for comparison experiments, and the results show that the improved algorithm has a greater advantage in mAP and 1-batch inference time(s).

Zhang et al.(2022) to achieve automatic surface crack detection and segmentation during bridge maintenance, the researchers establish a bridge surface crack dataset. To effectively detect the crack structure, they modified the CSPDarkNet53 structure of the YOLO algorithm and combined it with the PSPNet algorithm. The authors conducted comparative tests with Fast RCNN, YOLO v5s, U-Net, HRNet, and other algorithms, and the experimental results demonstrate the superior performance of this algorithm in generic evaluation metrics.

Table 9: Summary of the YOLO algorithm's Critical Analysis

Ref	Method	Backbone	Framework	Dataset	Surface	Loss Function	Optimizer	Annotation Tool	Performance
(Majidifard et al., 2020)	YOLO v2 U-net	-	-	PID	Asphalt	-	-	Manually	Overall precision = 93% Recall = 77% F1-score = 84%
(Park et al., 2020)	YOLOv3-tiny	-	TensorFlow	Own collection	Concrete	-	-	Manually	Accuracy = 94% Precision = 98%
(Du et al., 2021)	YOLO v3	-	-	PD	Asphalt	Squared error	SGD	labelImg	Accuracy = 73.64%
(Jiang et al., 2021)	Fast-YOLO	YOLO v3	-	Own collection	Concrete	-	Adam	LabelImg	Accuracy = 64.81%
(Li et al., 2021)	YOLO v3 YOLO v4 YOLO v5	-	PyTorch	Own collection	Asphalt	cross-entropy	-	LabelImg	mAP = 94.39%
(Tan et al., 2021)	YOLO v3	-	PyTorch	Own collection	Concrete	MSE	Adam	LabelImg	mAP = 92%
(Teng et al., 2021)	YOLO v2	-	MATLAB	Own collection	Concrete	Squared error	SGDM	Labeler	AP = 0.8
(Ma et al., 2022)	YOLO-MF	YOLO v3	-	CCIC	Concrete	-	-	LabelImg	Accuracy = 98.47%, F1 score = 0.958 mAP = 95.31% Precision = 97.34% Recall = 95.68% F1 score = 0.965
(Wu et al., 2022)	YOLOv4	-	PyTorch	Own collection	Concrete	CIoU loss	Adam	-	Precision = 90.88%, Recall = 88.69% F1 score = 89.77%
(Zhang et al., 2022)	CR-YOLO	YOLO v4	PyTorch	Own collection	Concrete	CIoU loss	Adam SGDM	-	

'-' denotes the journal article did not provide the particular information.

To explore the latest research progress in the YOLO algorithm, 94 journal articles on YOLO v8 were screened. Finally, 5 journal articles were screened as research directions for crack detection based on YOLO v8 algorithm. Next, the critical analysis of these 5 journal articles is carried out.

Zubayer et al.(2023) describe a method for quality inspection of metal direct additive manufacturing (DAM) samples using YOLO v8 to detect microstructures such as metal cracks and voids. Trained and tested on a publicly available, comprehensive dataset, the experimental results show a defect detection accuracy of 96%. The test results show that the method can effectively improve the accuracy and efficiency of quality inspection for additive manufacturing, making a significant contribution to the reliability and safety of various metal additive structures.

Chen et al.(2024) proposed an integrated framework for road crack data collection using UAVs

(unmanned aerial vehicle) for crack identification and evaluation using deep learning networks. In order to enhance the precision of fracture detection, the approach uses publicly available datasets (UAPD, RDD2022, UMSC, UAVRoadCrack, CrackForest, and self-constructed datasets) for model training and testing. according to the test findings, the YOLO v8 algorithm demonstrates the highest detection speed while maintaining a high level of accuracy in detection, which is suitable for lightweight deployment and application. The UAV platform will integrate the final detection algorithm in the future.

Hang et al.(2024) proposed the MIP-YOLO crack detection algorithm to detect damage in wind turbine fan blades, thereby improving their safety and stability. The authors introduce multivariate information perception, C2TR modules, Haar wavelet attention (HWA), C2fGhost, and C2CBAM to increase the accuracy of crack feature extraction and improve the detection of small targets. The Wise-IOU loss function is introduced to reduce the impact of low-quality samples on the model's performance. Trained and tested on a self-constructed dataset, the experimental results show that the method outperforms the existing algorithms in terms of crack classification, detection, and segmentation. This research provides an effective method for wind turbine blade crack detection and improves the operational efficiency of wind farms. Future work will focus on reducing information loss in feature extraction and implementing embedded programming for real-time detection.

Wang et al.(2024) used B-scan to collect internal crack images of rails and build a dataset. Training and testing of YOLOv5, YOLOv8, Faster R-CNN, and DETR models, used to select and build models that can accurately detect internal rail defects in real time. The experimental results show that the YOLO v8 algorithm can perform crack detection at a rate of three images per second with an average accuracy of 93.3%. The experimental results show that the YOLO v8 algorithm is suitable for real-time internal rail defect detection. Future work will focus on removing unnecessary convolutional layer structures from the deep learning network and exploring specific operations in the network that affect detection effectiveness.

Xiong et al.(2024) proposed that with the increasing popularity of vehicles and the increasing load of road traffic, the regular detection of bridge cracks is crucial for the safety of people and property. Therefore, an improved YOLO v8 algorithm is proposed to automate the detection of cracks in bridges. The model combines the General Attention Module and the Informed Intersection and Union (IoU) loss function, this enhances the precision and overall applicability of the detection. After being trained and tested on a dataset that was created by the authors, the experimental findings demonstrate that the algorithm performs better than the detection methods that already exist. Furthermore, the compact size of the model allows its use in portable detection devices.

Table 10: Summary of the YOLO v8's Critical Analysis

Ref	Method	Backbone	Framework	Dataset	Surface	Loss Function	Optimizer	Annotation Tool	Performance
(Zubayer et al., 2023)	YOLO v8	-	PyTorch 1.7	metal AM	Metal	BCE	-	LabelImg	Accuracy = 96%
(Chen et al., 2024)	YOLO v8	-	PyTorch	UAPD RDD2022 UMSC UAVRoadCrack CrackForest	Asphalt	cross-entropy	SGD	LabelImg	mAP = 77.1% F1-score = 75% FPS = 125.7 f. s ⁻¹

(Hang et al., 2024)	MIP-YOLO	YOLO v8	PyTorch	Own collection	Composite material	wise-IoU	SGD	Labelme	Accuracy = 98.7%
(Wang et al., 2024)	YOLO v8	-	Pytorch1.5	Own collection	Metal	cross-entropy IoU	-	LabelImg	Average precision = 93.3%
(Xiong et al., 2024)	YOLOv8 -GAM- Wise-IoU	YOLO v8	PyTorch	Own collection	Concrete	wise-IoU	-	LabelImg	Precision = 98.7%
									Recall = 95.1%
									F1 score = 0.97
									mAP = 99.1%

'-' denotes the journal article did not provide the particular information.

5. Conclusions

The authors have performed bibliometric and critical analysis of journal articles related to crack detection research based on YOLO algorithm. The bibliometric analysis shows that this field is in the rising stage of the industry, more and more researchers are flocking to this field; the journal Applied Sciences-Basel contains the most articles in this field; Teng Shuai and Dong Qiao are influential in this field; China dominates this field, working with the United States, the United Kingdom and Japan; The YOLO v5 algorithm is the most widely used generation; adding or modifying the attention mechanism is usually an important means to optimize the YOLO algorithm.

The critical analysis of the 10 most cited journal articles in the field shows that although the YOLO algorithm has evolved to YOLO v9, no researchers have applied YOLOv9 to the research field of crack detection, earlier versions of the YOLO algorithm are still more influential. Researchers typically run the YOLO algorithm in the PyTorch architecture, preferring to use custom datasets over public datasets; LabelImg is the most widely used annotation tool in the field, YOLO v5 is the most widely used algorithm, and optimizing the YOLO algorithm often involves adding or modifying the attention mechanism.

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