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# Recent advances in crack detection technologies for structures: a survey of 2022-2023 literature

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**Introduction:** Cracks, as structural defects or fractures in materials like concrete, asphalt, and metal, pose significant challenges to the stability and safety of various structures. Addressing crack detection is of paramount importance due to its implications for public safety, infrastructure integrity, maintenance costs, asset longevity, preventive maintenance, economic impact, and environmental considerations.

**Methods:** In this survey paper, we present a comprehensive analysis of recent advancements and developments in crack detection technologies for structures, with a specific focus on articles published between 2022 and 2023. Our methodology involves an exhaustive search of the Scopus database using keywords related to crack detection and machine learning techniques. Among the 129 papers reviewed, 85 were closely aligned with our research focus.

**Results:** We explore datasets that underpin crack detection research, categorizing them as public datasets, papers with their own datasets, and those using a hybrid approach. The prevalence and usage patterns of public datasets are presented, highlighting datasets like Crack500, Crack Forest Dataset (CFD), and Deep Crack. Furthermore, papers employing proprietary datasets and those combining public and proprietary sources are examined. The survey comprehensively investigates the algorithms and methods utilized, encompassing CNN, YOLO, UNet, ResNet, and others, elucidating their contributions to crack detection. Evaluation metrics such as accuracy, precision, recall, F1-score, and IoU are discussed in the context of assessing model performance. The results of the 85 papers are summarized, demonstrating advancements in crack detection accuracy, efficiency, and applicability.

**Discussion:** Notably, we observe a trend towards using modern and novel algorithms, such as Vision Transformers (ViT), and a shift away from traditional methods. The conclusion encapsulates the current state of crack detection research, highlighting the integration of multiple algorithms, expert models, and innovative data collection techniques. As a future direction, the adoption of emerging algorithms like ViT is suggested. This survey paper serves as a valuable resource for researchers, practitioners, and engineers working in the field of crack detection, offering insights into the latest trends, methodologies, and challenges.

KEYWORDS

**Cracks, structural defects, infrastructure integrity, preventive maintenance, economic impact, survey**

## 1 Introduction

Cracks are structural defects or fractures that occur in various materials, such as concrete, asphalt, and metal, often caused by stress, environmental factors, or wear over time. These imperfections can significantly compromise the integrity of structures, such as buildings, bridges, roads, and other infrastructures (Jiya et al., 2016). Understanding and addressing cracks is of paramount importance due to the following reasons:

Safety Concerns: Cracks in structures can pose severe safety hazards to the public. They weaken the structural stability, making buildings and bridges susceptible to collapse, potentially leading to injuries or loss of life.

Infrastructure Integrity: The presence of cracks can undermine the overall structural integrity of essential infrastructure. As cracks propagate and grow, they can weaken load-bearing elements, causing irreversible damage and costly repairs if not addressed promptly.

Maintenance Costs: Unchecked cracks can escalate maintenance costs significantly. Small cracks, when detected early, are easier and cheaper to repair than allowing them to worsen and cause extensive damage, requiring more extensive and costly rehabilitation.

Asset Longevity: Effective crack detection and timely repairs can extend the lifespan of structures. By addressing cracks early on, the overall durability and longevity of buildings and infrastructure can be significantly improved.

Preventive Maintenance: Crack detection plays a crucial role in implementing preventive maintenance strategies. Early identification allows for targeted repairs or reinforcement, preventing the cracks from spreading and mitigating potential risks.

Economic Impact: Infrastructure failure due to undetected cracks can result in significant economic losses. Repairs and structural rehabilitation can be costly, and in severe cases, infrastructure failures can disrupt transportation, utilities, and daily activities, impacting productivity and economic stability.

Environmental Impact: Cracked structures may allow for water ingress, leading to corrosion of reinforcement and other components. Water infiltration can further exacerbate cracks and compromise the structural integrity, impacting the environment and potentially leading to water-related issues like mold growth.

Given these critical implications, crack detection assumes immense significance in maintaining public safety, preserving infrastructure assets, and ensuring the efficient and sustainable operation of modern societies. Timely and accurate crack detection methods are vital tools for engineers, researchers, and practitioners, helping them assess structural health and make informed decisions to enhance the safety and longevity of our built environment.

In this survey paper, we focus on recent advancements and new developments in crack detection technologies for structures, with a specific emphasis on articles published in the years 2022 and 2023. To compile our findings, we conducted a thorough search of the Scopus database using the keywords "crack detection," "building," "road," "pavement," and "concrete." The search was further refined to include articles related to machine learning and deep learning techniques. The language criterion was set to English to ensure the coherence and consistency of the gathered information.

Our search yielded a total of 129 papers, of which 85 were closely aligned with our research focus. From Table 1 we can see the complete detail about the information from Scopus.

These articles serve as the foundation for our survey, enabling us to analyze the state-of-the-art developments and trends in crack detection within the context of structures. Additionally, we employed VOSviewer, a specialized software tool for bibliometric analysis, to generate keyword cloud maps, providing a visual representation of the prominent terms and concepts in the selected articles which it is obvious in Figure 1. It is clear that "Deep Learning" and,"Convolutional Neural Networks (CNN)" have the most relation with our main search topic "Crack Detection". Moreover, we have extracted valuable insights from the charts depicting "Documents by year," "Documents per year by source," "Documents by search area," and "Documents by country or territory," which contribute to our comprehensive understanding of the current landscape of crack detection research. As we can see from Figure 2 there are 78 papers which published in 2022 and 51 papers in 2023 up to now. We can see increment in the amount of the papers which published in "Sensors" and "Remote Sensing" in 2023 compare to 2022 due to the Figure 3. It is obviously clear that this search topic appears most in the fields of "Engineering" and "Computer Science", we can see this point from Figure 4. And from Figure 5 we can see the First 10 countries which published the papers in this field, more than the others.

Continuing with the survey paper, the subsequent sections delve into the methodologies used for crack detection. We explore traditional image processing techniques, such as edge detection, thresholding, and binary image analysis, highlighting their strengths and limitations. Additionally, we delve into the application of state-of-the-art deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Transformers, and other deep learning models, showcasing their superior performance and ability to capture intricate crack patterns (Golding et al., 2022; BaniMustafa et al., 2023).

Moving forward, we discuss potential future research directions in the field of crack detection. This includes the necessity for more diverse and comprehensive datasets, encompassing various types of structures, lighting conditions, and crack patterns (Sun et al., 2023).

TABLE 1 Summary of scopus query and search results.

| | |
|---|---|
| Query in Scopus | (TITLE-ABS-KEY ("crack detection" "deep learning") OR TITLE-ABS-KEY ("crack detection" "MachineLearning") OR TITLE-ABS-KEY ("crack detection" "building" "road" "pavement" "concrete")) AND PUBYEAR >2021 AND (LIMIT-TO (OA, "all")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) |
| Search Results | 129 |
| Unrelated Results | 44 |
| Related Results | 85 |

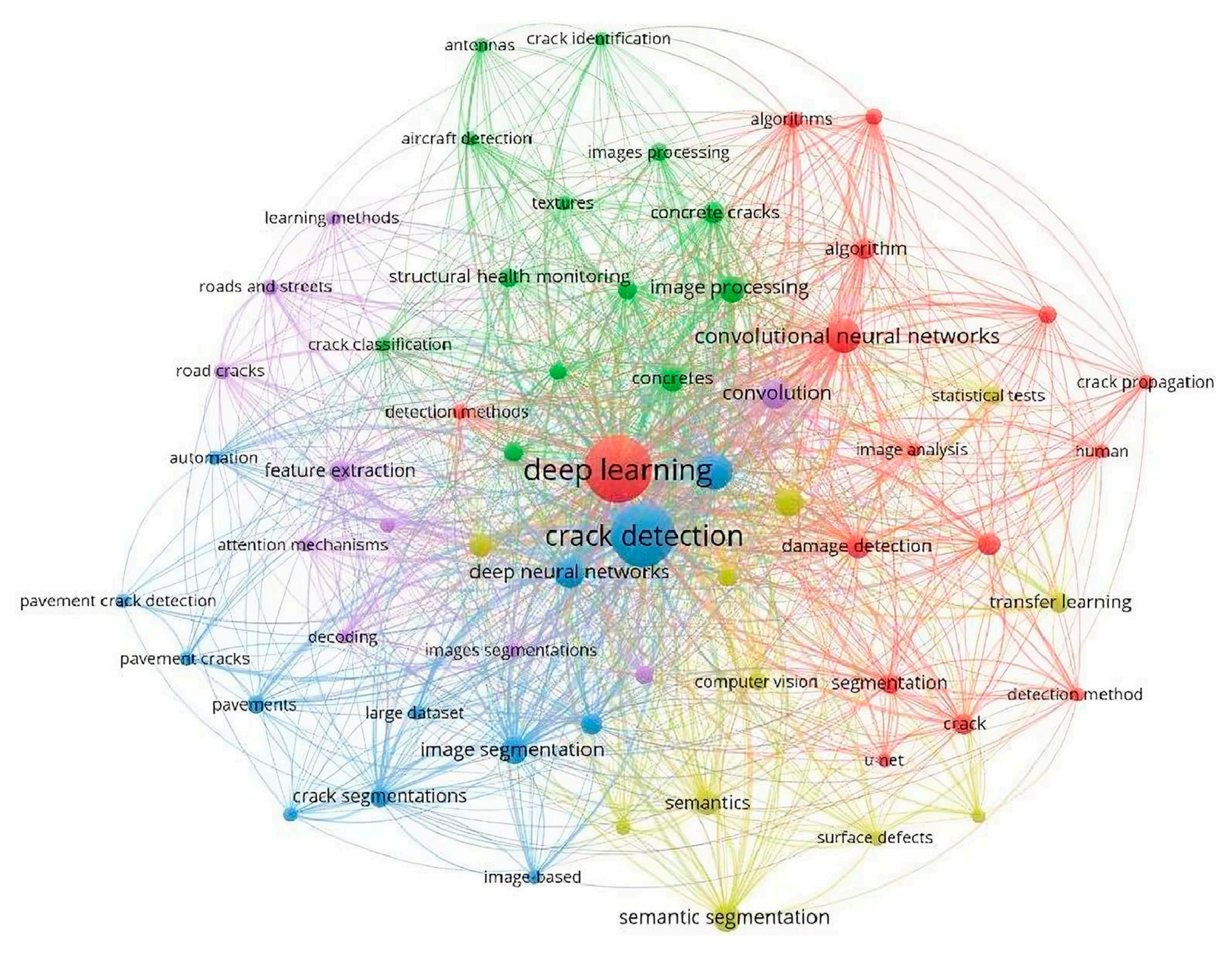


FIGURE 1
Keywords map by VOSviewer.

The survey paper also advocates for the development of real-time crack detection systems and the incorporation of explainable AI techniques to enhance the interpretability of crack detection models (Li G. et al., 2022; Ma D. et al., 2022).

In conclusion, this survey paper aims to be a valuable resource, consolidating the current knowledge on crack detection in structures. By reviewing both conventional and advanced techniques and providing insights into potential future developments, we aspire to inspire further advancements in this critical area, ultimately contributing to the safety, reliability, and longevity of vital infrastructures. To facilitate comprehension throughout the paper, we provide a list of acronyms along with their expanded forms which you can find it in Table 2.

# 2 The approach

## 2.1 Datasets in crack detection

In the realm of crack detection for various structures, the availability of diverse and appropriately curated datasets holds a pivotal role in advancing research and innovation. These datasets serve as the

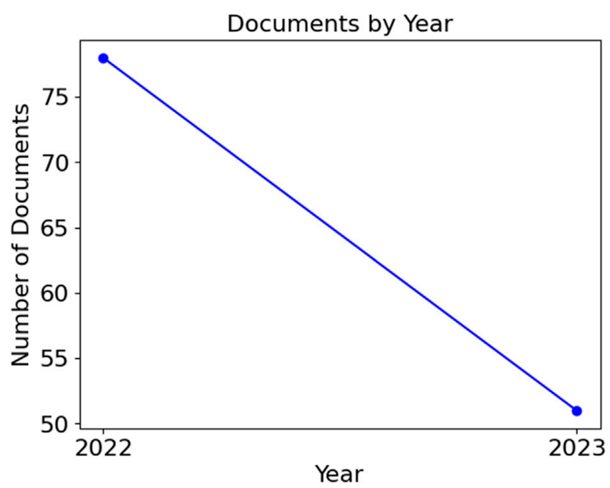


FIGURE 2
Documents per year by year.

foundation upon which crack detection models are trained, tested, and validated. A robust dataset ensures the realism and accuracy of the models, facilitating the development of effective and reliable crack detection methodologies. The creation and utilization of datasets in crack detection research encompass a wide spectrum of applications, from building and road infrastructure to pavements and concrete structures. These datasets encapsulate a range of crack types, sizes, orientations, and severity levels, mirroring the real-world scenarios that researchers and engineers encounter in practice. By incorporating the inherent complexity and variability of cracks, these datasets enable the evaluation and comparison of detection algorithms under diverse conditions. In the context of recent advancements, the integration of machine learning and deep learning techniques has spurred the demand for datasets that accommodate the unique challenges posed by these methods. Such datasets should not only represent structural defects accurately but also encompass a variety of environmental conditions, lighting variations, and perspectives, enhancing the models' adaptability and generalization capabilities. As we delve into the datasets utilized within the 85 papers reviewed in this survey, it becomes evident that researchers draw from a combination of sources to bolster the quality and comprehensiveness of their studies. Some papers leverage publicly available datasets, while others design and assemble their datasets, tailored to the specific objectives of their crack detection research. Moreover, a subset of studies combines both approaches, harnessing the power of existing public datasets and augmenting them with proprietary data to enhance the richness and diversity of training and testing scenarios. These datasets collectively contribute to the diversity and comprehensiveness of crack detection research. The subsequent sections of this paper delve into a detailed analysis of the datasets' origins and utilization. We categorize these datasets based on their sources and types, presenting a comprehensive overview of the dataset landscape. This analysis provides insights into the dataset selection and utilization practices that influence the evolution of crack detection technologies.

### 2.1.1 Public datasets

Publicly available datasets have played a crucial role in shaping the landscape of crack detection research. These datasets, carefully curated and made accessible to the research community, serve as valuable resources for benchmarking, testing, and validating crack detection algorithms. Researchers leverage these datasets to assess the performance of their methods and foster a collaborative environment

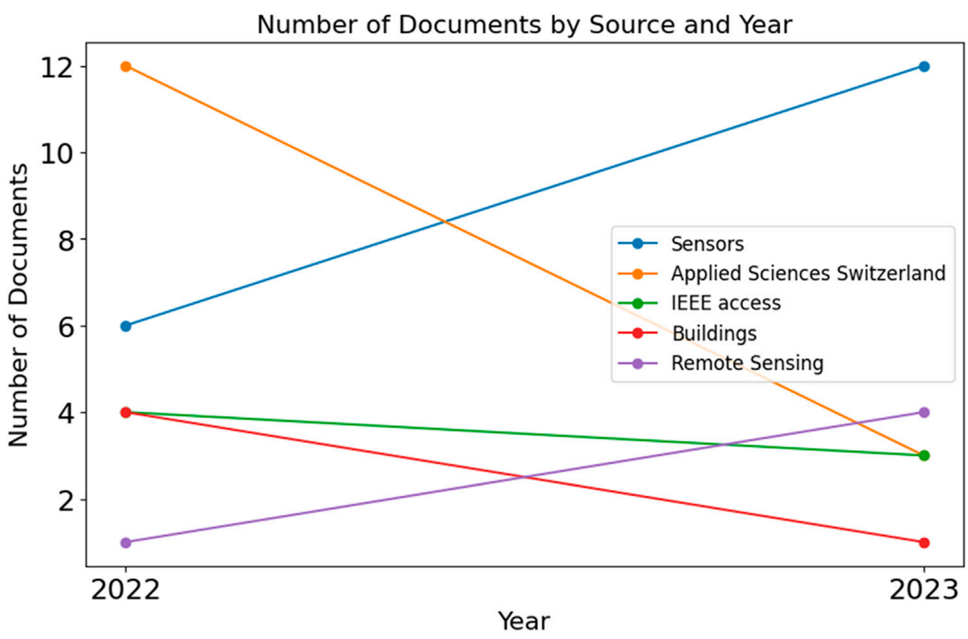


FIGURE 3
Documents per year by source.

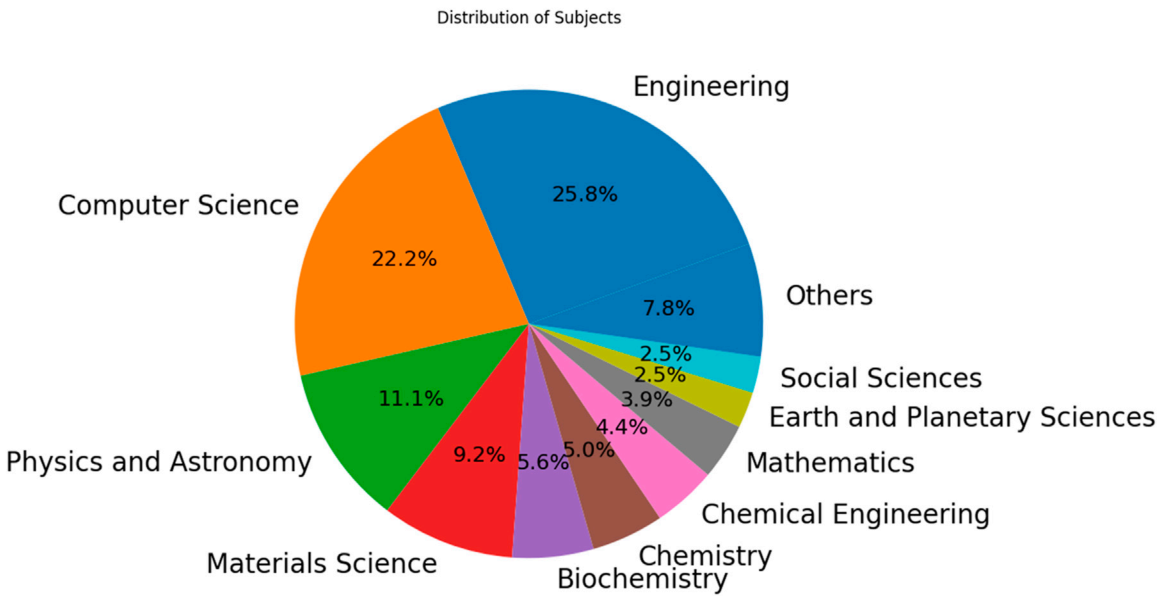


FIGURE 4
Documents by subject area.

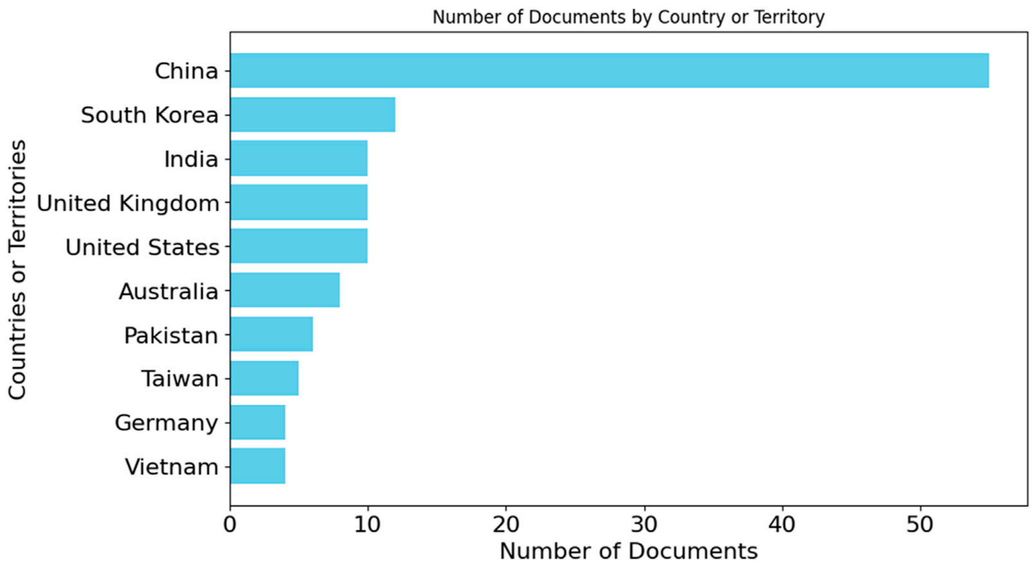


FIGURE 5
Documents by country or territory.

for advancing the field. In the pursuit of effective crack detection solutions, these datasets offer a diverse array of crack types, surface textures, and lighting conditions. The utilization of public datasets ensures a level playing field for researchers, enabling fair comparisons and promoting the development of innovative techniques. The following tables provide an overview of the distribution of papers per datasets and datasets per papers, shedding light on the prevalence and usage patterns of these publicly available resources. The datasets employed in these studies represent a diverse collection, each contributing to the advancement of crack detection technologies. Some of the prominent public datasets used in these papers include.

- Crack500: A dataset containing images of cracked and non-cracked concrete surfaces.
- Crack Forest Dataset (CFD): Images of cracked tree bark textures.
- CrackTree200: Images of tree bark with cracks for assessing detection techniques.
- Deep Crack: Images of various crack types for evaluating detection methods.
- GAPs384: Grayscale images containing cracks, patches, and non-defective areas for pavement crack detection.
- AigleRN: Images of cracks in road pavements for evaluation.
- CrackTree260: Tree bark images with cracks.

TABLE 2 List of acronyms used in this paper.

| Acronym | Expanded form | Acronym | Expanded form |
|---|---|---|---|
| CNN | Convolutional Neural Network | ANN | Artificial Neural Network |
| FCN | Fully Convolutional Network | ViT | Vision Transformer |
| SSD | Single Shot MultiBox Detector | CRF | Conditional Random Field |
| IoU | Intersection over Union | Rsef | Regional-Scale Edge Feature |
| mAP | Mean Average Precision | ResNet | Residual Neural Network |
| ROC | Receiver Operating Characteristic | UNet | U-Net |
| PR | Precision-Recall | YOLO | You Only Look Once |
| MCC | Matthews Correlation Coefficient | kNN | k-Nearest Neighbors |
| DCNN | Deep Convolutional Neural Network | GAN | Generative Adversarial Network |

- CRKWH100: Grayscale images of road surface cracks.
- CrackLS315: Images of cracked and non-cracked surfaces.
- RDD2022: Dataset focused on road damage detection, including cracks.
- DeepCrack537: Extended version of the Deep Crack dataset with a larger set of images.
- AED: Images of asphalt surfaces, including cracks.
- CrackSegNet: Dataset for evaluating the CrackSegNet model.
- DAGM 2007: Dataset used in image analysis and pattern recognition.
- CCIC: Dataset containing images of building cracks.
- CrackTree206: Additional tree bark images with cracks.
- SYCrack: Dataset used for crack detection research.
- Mixed Crack Dataset (MCD): Dataset containing mixed crack types.
- Building Wall Crack Images (BWCI): Images of cracks in building walls.
- SDNET2018: Comprehensive dataset for concrete crack detection.
- Crack45K: Large dataset with images of various crack types.
- Stone331: Dataset with images of stone surfaces and cracks.
- CQU-BPDD: Images of bridge pavement cracks.
- Historical Building Crack 2019: Dataset focusing on historical building cracks.

Table 3 shows the complete information about the public datasets which used in the studies.

### 2.1.2 Papers with their Own dataset

Some of the papers among the 85 reviewed in this survey have taken a proactive approach by creating their own datasets tailored to their research objectives. These researchers recognized the importance of aligning the dataset with the specific characteristics of their crack detection problem. By meticulously designing and curating their datasets, these studies aimed to capture the nuances of real-world scenarios, considering factors such as structural types, crack severity levels, lighting conditions, and surface textures. Creating a custom dataset offers several advantages. Researchers have the flexibility to control and manipulate variables to simulate a wide range of scenarios, contributing to a more controlled experimentation environment. Furthermore, custom datasets can address specific challenges or limitations present in publicly available datasets. However, this approach requires substantial effort in data collection, annotation, and validation, ensuring the dataset's integrity and applicability. The complete details of these proprietary datasets are presented in Table 4.

### 2.1.3 Papers using both their Own and public datasets

In the landscape of crack detection research, a subset of the reviewed papers stands out by leveraging a dual-source approach. These studies draw from the strengths of both their own meticulously curated datasets and publicly available datasets. By merging these sources, researchers aim to achieve a harmonious balance between dataset richness and diversity. The integration of proprietary and public datasets provides a unique opportunity for robust training and evaluation. Researchers benefit from the specificity and customization of their dataset while also capitalizing on the broader scope and variety offered by public datasets. This combination empowers researchers to validate the adaptability and generalization capabilities of their crack detection models across a spectrum of scenarios. Papers adopting this hybrid approach acknowledge the complementary nature of different datasets and recognize that collaborative efforts between proprietary and public sources can foster innovation and drive the advancement of crack detection techniques. For further insights into the specific datasets employed in these papers, refer to Table 5. These variations underscore the dynamic nature of crack detection research and highlight the multifaceted strategies researchers employ to overcome challenges and contribute to the evolution of structural health assessment technologies.

## 2.2 Algorithms and methods in Crack detection

The development and application of algorithms and methods in crack detection are central to the advancement of structural health assessment. As the field of crack detection has evolved, machine learning and deep learning techniques have emerged as powerful tools for automated crack detection, offering innovative solutions to the challenges posed by crack identification and characterization.

TABLE 3 Datasets and their brief explanation per papers.

| Dataset | Explanation | Paper | Type | Download link |
|---|---|---|---|---|
| Crack500 | Crack500 was curated by capturing 500 RGB color images featuring cracks on the surfaces of 500 asphalt roads, each with a resolution of 2560 × 1440. (Lee et al., 2023) | Munawar et al. (2022a), Mohammed et al. (2022), Yong and Wang (2022), Zhang et al. (2022), Zhao et al. (2023a), Lee et al. (2023), Yang et al. (2023) | Image | https://www.kaggle.com/datasets/pauldavid22/crack50020220509t090436z001 |
| Crack Forest Dataset (CFD) | The Crack Forest dataset comprises 118 pairs of RGB color images capturing asphalt road surface cracks in Beijing, China. These images were taken using an iPhone 5, and they maintain their original resolution of 480 × 320 pixels | Lee et al. (2023), Munawar et al. (2022b), Gooda et al. (2023), Inácio et al. (2023), Zhang et al. (2023a), Zhao et al. (2022), Jing et al. (2022), Zhao et al. (2023a), Li et al. (2022a) | Image | https://github.com/cuilimeng/CrackForest-dataset/tree/master |
| CrackTree200 | CrackTree200 offers high-resolution images at 800 × 600 pixels along with corresponding label values identifying surface cracks on asphalt surfaces. The dataset includes numerous images featuring cracks on asphalt surfaces with tree shadows. (Lee et al., 2023) | Zhao et al. (2023a), Lee et al. (2023), Lv et al. (2023) | Image | https://github.com/fyangneil/pavement-crack-detection/tree/master?tab=readme-ov-file |
| Deep Crack | The crack segmentation dataset encompasses 537 RGB color images, each with dimensions of 554 × 384 pixels. This dataset is characterized by its inclusion of images at various scales, showcasing cracks that can occur on surfaces composed of different materials. It features images depicting cracks on both concrete and asphalt surfaces. (Lee et al., 2023) | Lee et al. (2023), Zhang et al. (2022), Panta et al. (2023), de León et al. (2023), Jing et al. (2022) | Image | https://github.com/yhlleo/DeepCrack |
| GAPs384 | The German Asphalt Pavement Distress dataset comprises a collection of road surface images accompanied by labeling data, encompassing various distress types such as cracks, potholes, and inlaid paths. These images have a resolution of 1920 × 1,080 pixels, and the dataset consists of a total of 509 images. (Lee et al., 2023) | Li et al. (2022a), Munawar et al. (2022a), Zhao et al. (2023a), Lee et al. (2023), Lv et al. (2023) | Image | https://github.com/fyangneil/pavement-crack-detection/tree/master?tab=readme-ov-file |
| AigleRN | The dataset includes 38 pre-processed grayscale images depicting a road pavement surface located in France. This dataset is divided into two sets, with half of the images having dimensions of 991 × 462 pixels, and the remaining half having dimensions of 311 × 462 pixels. (Inácio et al., 2023) | Inácio et al. (2023) | Image | https://github.com/Sutadasuto/uvgg19_crack_detection?tab=readme-ov-file |
| CrackTree260 | The dataset comprises 260 images, each with dimensions of 800 × 600 pixels, captured using an area-array camera under visible light illumination conditions. (Inácio et al., 2023) | Inácio et al. (2023), Siriborvornratanakul (2022), Wang et al. (2022a) | Image | https://github.com/qinnzou/DeepCrack |
| CRKWH100 | The dataset includes 100 images of a road pavement surface, each with dimensions of 512 × 512 pixels, captured using a line array camera under visible light illumination conditions. (Inácio et al., 2023) | Inácio et al. (2023), Zhao et al. (2023b), Siriborvornratanakul (2022), Wang et al. (2022a) | Image | https://github.com/qinnzou/DeepCrack |
| CrackLS315 | The dataset comprises 315 images, each with dimensions of 512 × 512 pixels, captured using a line array camera under laser illumination. (Inácio et al., 2023) | Inácio et al. (2023), Zhao et al. (2023b), Siriborvornratanakul (2022), Wang et al. (2022a) | Image | https://github.com/qinnzou/DeepCrack |
| RDD2022 | The dataset includes 21,041 road damage images from Japan, the Czech Republic, and India, distributed as follows: 10,506 from Japanese pavement, 7,706 from Indian pavement, and 2,829 from Czech pavement. It covers various road conditions, comprising eight distinct categories, such as longitudinal cracks, transverse cracks, and crosswalk blur. (Yu and Zhou, 2023) | Liu et al. (2022), Ashraf et al. (2023), Yu and Zhou (2023) | Image | https://figshare.com/articles/dataset/RDD2022_-_The_multi-national_Road_Damage_Dataset_released_through_CRDDC_2022/21431547 |

(Continued on following page)

TABLE 3 (*Continued*) Datasets and their brief explanation per papers.

| Dataset | Explanation | Paper | Type | Download link |
|---|---|---|---|---|
| DeepCrack537 | This dataset consists of 537 images, each accompanied by annotated labels. All images and their corresponding labels share a uniform size of 544 × 384 pixels. (Zhang et al., 2023a) | Zhang et al. (2023a) | Image | Not Available |
| AED | The AED dataset consists of three sub-datasets: AigleRN (38 images), ESAR (15 images), and Dynamique (16 images). These images are unevenly illuminated and prone to noise interference, with mostly small cracks. (Zhang et al., 2023a) | Zhang et al. (2023a) | Image | https://universe.roboflow.com/ben-ohmju/aed-0awut/dataset/1 |
| CrackSegNet | The CrackSegNet dataset contains 919 crack images. (Yang et al., 2023) | Yang et al. (2023) | Image | Not Available |
| DAGM 2007 | The DAGM 2007 dataset is organized into 10 classes, with 6 classes designated for development and 4 classes for the 2007 DAGM sym- posium competition. In the initial 6 classes, there are 1,000 nondefective images and 150 defective images each, while the remaining 4 classes comprise 2,000 nondefective and 300 defective images per class. Each class is generated using distinct texture and defect models. (Kim et al., 2023b) | Kim et al. (2023b) | Image | https://www.kaggle.com/datasets/mhskjelvareid/dagm-2007-competition-dataset-optical-inspection |
| CCIC | This dataset comprises concrete images with cracks collected from various METU Campus Buildings, divided into negative and positive crack images for classification. Each class contains 20,000 images, totaling 40,000 images with dimensions of 227 × 227 pixels in RGB. It originates from 458 high-resolution images (4032 × 3024 pixels) using (Zhang et al., 2016)'s method. The high-resolution images exhibit variations in surface finish and illumination conditions. No data augmentation techniques, such as random rotation or flipping, are employed | Ozgenel and Sorguç (2018), Wang et al. (2022b), Golding et al. (2022), Islam et al. (2022), Jayaraju et al. (2022), Paramanandham et al. (2022), Pu et al. (2022), Bai et al. (2023), Shim et al. (2023) | Image | https://www.kaggle.com/datasets/arnavr10880/concrete-crack-images-for-classification |
| CrackTree206 | The dataset consists of 206 images of road cracks, each with a resolution of 800 × 600 pixels, and may contain occlusions and shadows. (Zhang et al., 2022) | Zhang et al. (2022) | Image | https://github.com/qinnzou/DeepCrack |
| SYCrack | There are 177 images, all sized uniformly at 256,256 pixels, which were captured from cracks on the Suoyang Ancient City wall surface. (Zhang et al., 2022) | Zhang et al. (2022) | Image | Not Available |
| Mixed Crack Dataset (MCD) | The MCD dataset comprises a total of 2,538 raw images along with their corresponding annotations. These images encompass concrete cracks, asphalt cracks, and earthen cracks, sourced from datasets such as CrackTree206, Crack500, Deep Crack, and SYCrack. (Zhang et al., 2022) | Zhang et al. (2022) | Image | Not Available |
| Building Wall Crack Images (BWCI) | BWCI consists of 4,500 wall crack images with 27 27 pixels. (Islam et al., 2022) | Islam et al. (2022) | Image | Not Available |
| SDNET2018 | SDNET2018 is an extensive dataset consisting of more than 56,000 images capturing both cracked and non-cracked concrete bridge decks, walls, and pavements. Notably, the dataset encompasses cracks ranging from as narrow as 0.06 mm to as wide as 25 mm. (Dorafshan et al., 2018) | Lv et al. (2023), Ngo et al. (2023), Philip et al. (2023), Qayyum et al. (2023), Lu et al. (2022), Inam et al. (2023), Kao et al. (2023), Shim et al. (2023), Li et al. (2023a), Popli et al. (2023) | Image | https://www.kaggle.com/datasets/aniruddhsharma/structural-defects-network-concrete-crack-images |

(Continued on following page)

TABLE 3 (*Continued*) Datasets and their brief explanation per papers.

| Dataset | Explanation | Paper | Type | Download link |
|---|---|---|---|---|
| Crack45K | The dataset comprises 45,000 images, each with a resolution of 224 × 224 pixels, showcasing diverse pavement surfaces, both with and without cracks. (Ali et al., 2022) | Ali et al. (2022) | Image | Not Available |
| Stone331 | The dataset consists of 331 grayscale images of stone surfaces, each with a size of 512,512 pixels. It's worth noting that the entire image may not contain the stone, so masks are provided to exclude predictions outside the stone area. (Konig et al., 2021; Siriborvornratanakul, 2022) | Siriborvornratanakul (2022) | Image | https://github.com/qinnzou/DeepCrack |
| CQU-BPDD | The CQU-BPDD consists of 60,056 bituminous pavement images captured by in-vehicle cameras on a professional pavement inspec- tion vehicle in southern China. Each image corresponds to a 2 × 3 meters pavement patch on highways and has a resolution of 1200900 pixels. The dataset includes seven distress types: transverse crack, massive crack, alligator crack, crack pouring, longitudinal crack, ravelling, repair, and normal pavement conditions. (Tang et al., 2021) | Liu et al. (2022) | Image | https://github.com/DearCaat/CQU-BPDD |
| Historical Building Crack 2019 | This dataset comprises 3,886 images, including annotated RGB images, with 757 depicting cracks and 3,139 depicting non-crack conditions. The raw images were captured using a Canon camera (Canon EOS REBEL T3i) with a resolution of 5184 × 3456 pixels. These images feature historical buildings, such as the Mosque (Mas- jed) of Amir al-Maridani, situated in Sekat Al Werdani, El-Darb El-Ahmar, in the Cairo Governorate. (Yadav et al., 2022) | Yadav et al. (2022) | Image | https://data.mendeley.com/datasets/xfk99kpmj9/1 |

### 2.2.1 Machine learning methods

Machine learning techniques encompass a range of methodologies that enable computers to learn patterns and make predictions from data without being explicitly programmed. These methods leverage statistical algorithms to recognize patterns and trends, making them well-suited for analyzing crack patterns and textures in images. One key advantage of machine learning is its versatility in handling various types of data and extracting relevant features for crack detection. However, the effectiveness of traditional machine learning methods can be limited by their dependence on hand-crafted features and their inability to capture complex spatial relationships within cracks.

### 2.2.2 Deep learning

Deep learning, a subset of machine learning, has gained immense popularity in recent years due to its ability to automatically learn hierarchical representations from raw data. Deep learning models, such as convolutional neural networks (CNNs), have demonstrated remarkable success in image classification, object detection, and segmentation tasks. CNNs excel at capturing intricate features and patterns within images, making them particularly well-suited for crack detection. Deep learning methods often outperform traditional machine learning approaches by automatically learning relevant features from data, eliminating the need for manual feature engineering. However, deep learning models typically require large amounts of labeled data and significant computational resources for training.

### 2.2.3 Convolutional neural networks (CNNS)

CNNs are a class of deep neural networks specifically designed for processing grid-like data, such as images. They consist of multiple layers, including convolutional, pooling, and fully connected layers, which extract progressively abstract features from input images. CNNs have shown remarkable performance in various computer vision tasks, including crack detection, by automatically learning and capturing complex visual patterns within crack images. The hierarchical structure of CNNs allows them to identify local features as well as global patterns, making them a suitable choice for crack identification and classification.

Advantages of CNNs in Crack Detection Hierarchical Feature Learning: CNNs can automatically learn and represent hierarchical features within images, capturing intricate patterns and textures characteristic of cracks. Local and Global Context: CNNs can simultaneously capture local and global contextual information, aiding in accurate crack identification. Robustness: CNNs are robust to variations in lighting, orientation, and noise, making them suitable for real-world crack detection scenarios. Disadvantages of CNNs in Crack Detection:

Data Requirements: CNNs require a large amount of labeled training data to generalize well to diverse crack patterns and

TABLE 4 Papers with their own datasets.

| Paper | Their own dataset |
|---|---|
| Li et al. (2022b) | This study employed image data obtained from CiCS, a rapid road condition detection system in China. The dataset consisted of 1,923 pavement cracking images in "jpg" format, each with a resolution of 96 dpi (3,024 × 1887 pixels). Out of these, 1,538 images were allocated for training, while the remaining 385 were designated for testing |
| Yang et al. (2022) | The dataset comprised 10,400 images acquired by a vehicle equipped with a highway condition monitor, encompassing a total of 202,840 labeled instances of pavement distress |
| Lee et al. (2022) | The dataset consisted of 4,000 images, equally divided into 2,000 negative and 2,000 positive samples |
| Mo et al. (2022) | The hazardous clearance set comprised 1,200 samples, while the non-hazardous clear-ance set contained 800 samples |
| Li et al. (2022c) | The dataset consisted of 600 images captured using the Teledyne Dalsa S3-24-02k40, a high-speed linear array industrial digital camera |
| Zhang et al. (2023b) | The dataset comprises approximately 800 photos of bridge cracks, collected manually using a digital camera with a resolution of 1,664 × 1,664 pixels in JPG format. In total, 4,033 images were labeled, capturing various weather conditions |
| Ha et al. (2022) | Total 6,650 images |
| Maslan and Cicmanec (2023) | Total 3,279 images |
| Loverdos and Sarhosis (2022) | Total 107 fully annotated images of masonry structures |
| Wibowo et al. (2022) | Total 2,516 images obtained through web scraping |
| Wang (2023) | The dataset initially consisted of 284 images, each with a resolution of 1706 × 1,280 pixels and 8 bits per channel in RGB format, captured on the campus of Hefei University using a smartphone. After applying augmentation techniques, the dataset expanded to encompass 6,000 images |
| Xu et al. (2022) | The dataset comprised 148 images of pavement cracks, which were captured using smartphones and covered various types of cracks. Additionally, data augmentation techniques were applied to expand the dataset by 50% |
| Kapadia et al. (2023) | The dataset was meticulously curated, containing over 80,000 images of cracks and an equal number of non-crack images sourced from concrete cube surfaces |
| Ma et al. (2022b) | The MaDataSet, a collection of 474 images depicting cracks in ancient timber structures, was compiled from the Bawang Academy at Shen-yang Jianzhu University |
| Wan et al. (2022) | The dataset comprised more than 300 crack images from the Jing-Hang Grand Canal<br>Extra Large Bridge site and over 1,500 crack images from the laboratory. Following data augmentation, the total image count expanded to 7,000 |
| Ren et al. (2022) | A high-resolution camera, affixed to a vehicle, gathered 9,650 images portraying diverse pavement cracks for the dataset. |
| Elghaish et al. (2022) | The dataset comprised 4,663 images of highway cracks, categorized into three groups<br>"vertical cracks," "horizontal and vertical cracks," and "diagonal cracks." |
| Chu et al. (2023) | Total 6,000 images from Pakistani roads |
| Wu et al. (2022) | 125 images of cracked concrete with dimensions measuring 3120 × 4160 pixels |
| Nomura et al. (2022) | Totally around 100,000 images |
| Yu et al. (2022) | 437 RGB images with their segmentation labels |
| Yu et al. (2022) | The dataset comprises 1,000 digital photos captured using a Canon EOS 5DS R camera during regular bridge inspections. Among these photos, 487 contained cracks, and through augmentation techniques, this number was expanded to 3,365 images |
| Munawar et al. (2022a) | The benchmarking dataset included 600 images depicting damage to buildings located in Sydney |
| Kun et al. (2022) | The dataset consisted of 385 images of bridges taken at Zhongshan Bridge in Gansu<br>China, using an I-800 Airborne Plane Array Camera |
| Kolappan Geetha et al. (2023) | The dataset used to train the 1D DFT-CNN model consisted of 1,492 images containing cracks and 1,321 images without cracks on concrete surfaces, encompassing diverse optical conditions |
| Hammouch et al. (2022) | The dataset was generated from video frames supplied by the Moroccan National<br>Center for Road Studies and Research (CNER) through the SMAC system, leading to a collection of 3,287 images that were manually annotated |
| Deng et al. (2023) | Total 6,840 images |
| Tan and Dong (2023) | The dataset was thoughtfully curated to include 2000 images, primarily due to hardware (GPU) constraints. Segmentation masks were generated using LabelImgPlus |
| Paramanandham et al. (2023) | The authors utilized their own dataset for their research |

(Continued on following page)

TABLE 4 (*Continued*) Papers with their own datasets.

| Paper | Their own dataset |
|---|---|
| Lee and Huh (2022) | Total 800 multisensory images |
| Kim et al. (2022) | The wall quality dataset consisted of 5,000 images showcasing various defects such as cracks, holes, efflorescence, damp patches, and spall issues, with 1,000 images dedicated to each category |
| Kou et al. (2022) | The dataset encompassed 380 images of rail cracks, gathered over a year in diverse weather, traffic, and wear conditions |
| Yuan et al. (2022) | 300 self-captured pavement crack images |
| Liu et al. (2023) | Total 21,547 images |
| Guo et al. (2023) | Total 88 images |
| Li et al. (2023b) | The dataset was generated from drone-captured rock mass crack images, resulting in a VOC dataset that employed advanced data augmentation techniques |
| Kim et al. (2023a) | The image dataset was sourced from the Korea Expressway Corporation's bridge monitoring system, consisting of a total of 192 images |
| Tse et al. (2023) | The dataset included 4,000 crack images, covering nine distinct crack types with different orientations |
| Lee and Yoo (2023) | The crack dataset consisted of 11,226 image sets along with corresponding masks, facilitating precise crack detection and non-semantic object removal |
| Quqa et al. (2022) | A dataset comprising images of welding joints from a long-span steel bridge, captured using high-resolution consumer-grade digital cameras |
| Ji et al. (2022) | Total 11,449 images, including 4,650 pavement and 6,799 concrete images |
| Chen et al. (2022) | Total 1,452 images |

TABLE 5 Papers with Public dataset and their own dataset.

| Paper | Public dataset + their own dataset |
|---|---|
| Ashraf et al. (2023) | This study utilized data from two sources: RDD2022, a publicly available online dataset, and a second set of data collected from the roads of Malaysia |
| Yong and Wang (2022) | 727 images by 4-megapixel Hikvision industrial camera MV-CA060–10 GC and Crack500 dataset |
| Lee et al. (2023) | A total of 1,235 test images were obtained from drone footage on the sea bridge, in addition to 10,789 open images sourced from datasets including Crack Forest Dataset, Crack500, CrackTree200, Deep Crack, and GAPs384 |
| Zhao et al. (2023b) | UAVRoadCrack, and public datasets: CRKWH100, and CrackLS315 Total 7,403 images |
| Munawar et al. (2022b) | All the self-built dataset images were acquired using the DJI-M200 UAV, which utilizes vertical take-off and landing (VTOL) technology. This dataset amalgamated data from Crack Forest Dataset (CFD), Crack500, and GAPs, resulting in a comprehensive collection of 1,300 images |
| Kang and Cha (2022) | A total of 1,203 images were included in the dataset, and they underwent extensive augmentation using synthesis techniques. Additionally, the dataset was evaluated using 545 testing images sourced from both existing datasets and their proprietary data |
| Panta et al. (2023) | The dataset of levee crack images was gathered over several years by field inspectors from the New Orleans district of the U.S. Army Corps of Engineers (USACE). Initially, it contained 1,650 images. To enhance the dataset, 101 additional levee crack images were annotated using the VGG Image Annotator tool. For comprehensive model analysis, the DeepCrack road crack dataset was also utilized. This dataset's test subset comprised 237 images, each accompanied by its respective masks |
| Inam et al. (2023) | Self-built dataset from Pakistan and the SDNET2018 dataset |
| Kao et al. (2023) | Crack images were sourced from various devices, including smartphones, a camera mounted on a UAV (Unmanned Aerial Vehicle), and the open-source deep-learning dataset SDNET2018 |
| Li et al. (2022a) | A total of 48,000 images were used, including those generated through augmentation (from a self-created dataset), and the Crack Forest Dataset (CFD) and GAPs images were included for evaluation |

variations. Computational Intensity: Training and fine-tuning CNNs can be computationally intensive, necessitating powerful hardware and resources. Interpretability: The inner workings of CNNs can be challenging to interpret, limiting their explainability in critical applications. In the 85 articles surveyed, a diverse array of algorithms and methods were employed for crack detection. Notably, the following algorithms emerged as prominent choices, showcasing their effectiveness in addressing the intricacies of crack identification and classification:

CNN (Convolutional Neural Networks): CNNs, as previously discussed, are widely used for crack detection due to their ability to capture complex patterns and textures in images. They have been

TABLE 6 Main Algorithms with their related papers.

| Algorithm | Paper |
|---|---|
| CNN | Yang et al. (2023), Chu et al. (2023), Inácio et al. (2023), de León et al. (2023), Guo et al. (2023), Kim et al. (2023a), Lee and Yoo (2023), Jayaraju et al. (2022), Lee et al. (2022), Yong and Wang (2022), Wu et al. (2022), Lu et al. (2022), Quqa et al. (2022), Chen et al. (2022), Yadav et al. (2022), Golding et al. (2022), Wang et al. (2022a) |
| Deep Learning | Golding et al. (2022), Kou et al. (2022), Kun et al. (2022), Liu et al. (2022), Pu et al. (2022), Wan et al. (2022), Kolappan Geetha et al. (2023), Liu et al. (2023), Ngo et al. (2023), Popli et al. (2023), Shim et al. (2023), Yang et al. (2023) |
| YOLO | Ashraf et al. (2023), Zhang et al. (2023b), Maslan and Cicmanec (2023), Gooda et al. (2023), Deng et al. (2023), Yu and Zhou (2023), Inam et al. (2023), Li et al. (2023b), Tse et al. (2023), Kao et al. (2023), Xu et al. (2022), Li et al. (2022b), Yang et al. (2022), Ma et al. (2022b), Ren et al. (2022), Nomura et al. (2022), Yu et al. (2022) |
| UNet | Kim et al. (2023b), Gooda et al. (2023), Bai et al. (2023), Deng et al. (2023), Inam et al. (2023), Zhao et al. (2023a), Li et al. (2023a), Wang et al. (2022b), Li et al. (2022c), Ha et al. (2022), Loverdos and Sarhosis (2022), Mohammed et al. (2022), Jing et al. (2022), Ji et al. (2022), Wang et al. (2022a) |
| ResNet | Wang et al. (2022a), Islam et al. (2022), Ji et al. (2022), Kim et al. (2022), Paramanandham et al. (2022), Siriborvornratanakul (2022), Wibowo et al. (2022), Li et al. (2023a), Bai et al. (2023), Deng et al. (2023), Paramanandham et al. (2023), Qayyum et al. (2023) |
| Rsef | Kim et al. (2023b) |
| Ensemble Learning | Lee et al. (2023) |
| CrackNet | Gharehbaghi et al. (2022), Zhao et al. (2023b) |
| Mask RCNN | Lv et al. (2023), Xu et al. (2022) |
| Fast RCNN<br>CrackSN | Mo et al. (2022), Xu et al. (2022), Zhao et al. (2022)<br>Wang (2023) |
| Inceptionv3 | Kapadia et al. (2023), Paramanandham et al. (2023), Qayyum et al. (2023) |
| IterLUNet | Panta et al. (2023) |
| VGG | Wang et al. (2022a), Elghaish et al. (2022), Hammouch et al. (2022), Islam et al. (2022), Ji et al. (2022), Nomura et al. (2022), Paramanandham et al. (2022), Wibowo et al. (2022), Zhang et al. (2022), Guo et al. (2023), Paramanandham et al. (2023), Philip et al. (2023) |
| MobileNet | Ha et al. (2022), Philip et al. (2023), Qayyum et al. (2023) |
| Xception | Philip et al. (2023) |
| GoogleNet | Qayyum et al. (2023), Elghaish et al. (2022) |
| ShuffleNet | Qayyum et al. (2023) |
| Omni-Dimensional Dynamic Convolution | Tan and Dong (2023) |
| PIRM | Paramanandham et al. (2023) |
| CTCD-Net | Zhang et al. (2023a) |
| DenseNet | Li et al. (2022a), Wang et al. (2022a), Islam et al. (2022) |
| AlexNet | Elghaish et al. (2022), Islam et al. (2022), Paramanandham et al. (2022) |
| SqueezeNet | Ha et al. (2022), Wang (2023) |
| DeepLab | Loverdos and Sarhosis (2022), Wang et al. (2022a), Siriborvornratanakul (2022), Yu et al. (2022) |
| LinkNet | Loverdos and Sarhosis (2022) |
| FPN | Loverdos and Sarhosis (2022) |
| ViT | Ali et al. (2022) |
| Adversarial Network | Munawar et al. (2022a), Yuan et al. (2022) |
| STRNet | Kang and Cha (2022) |

applied in various architectures and configurations to achieve high accuracy in crack identification.

Deep Learning: Deep learning approaches beyond CNNs have been leveraged to enhance crack detection:

YOLO (You Only Look Once): YOLO is a real-time object detection algorithm that can identify and locate multiple objects in an image simultaneously. It has been adapted for crack detection to provide efficient and accurate localization of cracks within images.

TABLE 7 Algorithms used in 85 articles.

| # | Paper | Algorithm |
|---|---|---|
| 1 | Ashraf et al. (2023) | Custom YOLOv7 |
| 2 | Yang et al. (2023) | Deep CNN |
| 3 | Kim et al. (2023b) | Rsef based on U-net namely, Rsef-Edge |
| 4 | Lee et al. (2023) | Ensemble learning |
| 5 | Zhang et al. (2023b) | Yolo v4 |
| 6 | Zhao et al. (2023b) | CrackNet |
| 7 | Maslan and Cicmanec (2023) | YOLO v2 |
| 8 | Lv et al. (2023) | Mask R-CNN |
| 9 | Wang (2023) | CrackSN built on the Adam-SqueezeNet architecture |
| 10 | Gooda et al. (2023) | EfficientNet with residual U-Net for segmentation, YOLO v5 for crack detection |
| 11 | Kapadia et al. (2023) | The Inceptionv3 model |
| 12 | Ngo et al. (2023) | Deep learning |
| 13 | Chu et al. (2023) | CNN |
| 14 | Bai et al. (2023) | ResNet and ResNet + UNet |
| 15 | Kolappan Geetha et al. (2023) | Deep Learning |
| 16 | Panta et al. (2023) | Iterative Loop UNet (IterLUNet) |
| 17 | Philip et al. (2023) | VGG16, VGG19, ResNet 50, MobileNet, and Xception |
| 18 | Qayyum et al. (2023) | GoogLeNet, MobileNet-V2, Inception-V3, ResNet18, ResNet50, ResNet101, and ShuffleNet |
| 19 | Inácio et al. (2023) | Multi-class CNN |
| 20 | Deng et al. (2023) | YOLOv5 crack detection and Res-UNet segmentation |
| 21 | Tan and Dong (2023) | A pyramidal residual network, employing an encoder-decoder architecture, incorporates Omni Dimensional Dynamic Convolution for its operations |
| 22 | Paramanandham et al. (2023) | The Pixel-Intensity Resemblance Measurement (PIRM) rule was applied in conjunction with VGG-16, ResNet-50, and InceptionResNet-V2 models for the purpose of crack detection |
| 23 | Yu and Zhou (2023) | A novel approach for crack detection, named YOLOv5-CBoT, is introduced by enhanc-ing the YOLOv5 network with a Bottleneck Transformer |
| 24 | Zhang et al. (2023a) | CTCD-Net: A Cross-layer Transmission network for tiny road Crack Detection |
| 25 | de León et al. (2023) | A novel crack segmentation algorithm has been developed, which combines the theory of minimal path selection with a region-based approach. This method involves the segmentation of texture features extracted using Gabor filters |
| 26 | Inam et al. (2023) | YOLOv5 for crack detection and U-Net for segmentation |
| 27 | Liu et al. (2023) | Deep convolutional network (Single Shot MultiBox Detector (SSD)) |
| 28 | Guo et al. (2023) | Adopted convolutional neural network (CNN) (VGG16 + Focal Loss) |
| 29 | Li et al. (2023b) | The YOLOv7 with attention mechanism |
| 30 | Kim et al. (2023a) | CNN |
| 31 | Tse et al. (2023) | Improved YOLOv4 with an attention module |
| 32 | Kao et al. (2023) | YOLOv4 |
| 33 | Lee and Yoo (2023) | Fast encoder-decoder network with scaling attention |
| 34 | Zhao et al. (2023a) | U-Net |
| 35 | Shim et al. (2023) | A novel deep neural network has been introduced, accompanied by an adversarial learning-based balanced ensemble discriminator network |
| 36 | Li et al. (2023a) | Segmentation by ResNet50 as a UNet model |

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TABLE 7 (*Continued*) Algorithms used in 85 articles.

| # | Paper | Algorithm |
|---|---|---|
| 37 | Popli et al. (2023) | Deep learning |
| 38 | Xu et al. (2022) | Fast RCNN, Mask RCNN and compare with YOLO. |
| 39 | Jayaraju et al. (2022) | CNN |
| 40 | Zhang et al. (2022) | FPN-vgg16 |
| 41 | Wang et al. (2022b) | U-Net and the dual-attention network (DANet), and efficient mobile-attention X-network (MA-Xnet) |
| 42 | Li et al. (2022b) | YOLOv4-3 |
| 43 | Yang et al. (2022) | YOLOv5s |
| 44 | Lee et al. (2022) | CNN |
| 45 | Mo et al. (2022) | Fast R-CNN |
| 46 | Yong and Wang (2022) | An end-to-end real-time pavement crack segmentation network, denoted as RIIAnet, has been developed |
| 47 | Li et al. (2022c) | U-Net and a side-output part: SoUNet |
| 48 | Islam et al. (2022) | VGG16, ResNet18, DenseNet161, and AlexNet |
| 49 | Ha et al. (2022) | SqueezeNet, U-Net, and Mobilenet-SSD |
| 50 | Loverdos and Sarhosis (2022) | U-Net, DeepLabV3+, U-Net (SM), LinkNet (SM), and FPN (SM) |
| 51 | Ali et al. (2022) | The vision-transformer (ViT) |
| 52 | Wibowo et al. (2022) | VGG16 and RestNET50 |
| 53 | Pu et al. (2022) | Deep convolutional neural network (DCNN) |
| 54 | Munawar et al. (2022b) | Cycle generative adversarial network (CycleGAN) |
| 55 | Ma et al. (2022b) | YOLO v3, YOLO v4s-mish, and YOLO v5s |
| 56 | Wan et al. (2022) | Deep Learning |
| 57 | Ren et al. (2022) | YOLOV5 |
| 58 | Kang and Cha (2022) | Semantic transformer representation network (STRNet) |
| 59 | Siriborvornratanakul (2022) | DeepLabV3-ResNet101 |
| 60 | Elghaish et al. (2022) | AlexNet, VGG16, VGG19, GoogleNet. |
| 61 | Wu et al. (2022) | Full convolutional neural networks FCN-8s, FCN-16s, and FCN-32s |
| 62 | Liu et al. (2022) | Deep Domain Adaptation-based Crack Detection Network (DDACDN) |
| 63 | Nomura et al. (2022) | YOLOv2 + VGG16 |
| 64 | Yu et al. (2022) | DeepLabV3+ |
| 65 | Yu et al. (2022) | YOLOv5 |
| 66 | Munawar et al. (2022a) | CNN and a cycle generative adversarial network (CycleGAN) |
| 67 | Kun et al. (2022) | Deep bridge crack classification (DBCC)-Net |
| 68 | Mohammed et al. (2022) | U-Net |
| 69 | Hammouch et al. (2022) | VGG-19 |
| 70 | Lee and Huh (2022) | This study introduces a dataset. |
| 71 | Lu et al. (2022) | Multi-scale crack detection network: MSCNet |
| 72 | Kim et al. (2022) | Conv2D ResNet. |
| 73 | Kou et al. (2022) | Deep Learning |
| 74 | Zhao et al. (2022) | Fast R-CNN |

(Continued on following page)

TABLE 7 (*Continued*) Algorithms used in 85 articles.

| # | Paper | Algorithm |
|---|---|---|
| 75 | Jing et al. (2022) | AR-UNet based on UNet |
| 76 | Gharehbaghi et al. (2022) | FastCrackNet |
| 77 | Yuan et al. (2022) | Generative adversarial network |
| 78 | Paramanandham et al. (2022) | Alexnet, VGG16, VGG19 and ResNet-50 |
| 79 | Quqa et al. (2022) | CNN |
| 80 | Ji et al. (2022) | U-Net. ResUNet, VGGU-Net, and EfficientU-Net. |
| 81 | Chen et al. (2022) | Enhanced graph network branch |
| 82 | Yadav et al. (2022) | Multi-scale feature fusion (3SCNet + LBP + SLIC) |
| 83 | Golding et al. (2022) | Deep learning-based autonomous crack detection method using CNN |
| 84 | Li et al. (2022a) | Dense boundary refinement network (DBR-Net) |
| 85 | Wang et al. (2022a) | Several semantic segmentation models were explored, including Fully Convolutional Network (FCN), Global Convolutional Network (GCN), Pyramid Scene Parsing Net- work (PSPNet), UPerNet, and DeepLabv3+. These models were coupled with various backbone architectures, including VGG, ResNet, and DenseNet, to investigate their performance |

UNet: UNet is a convolutional neural network architecture designed for biomedical image segmentation. Its U-shaped architecture enables precise segmentation of crack regions, making it well-suited for crack detection and localization.

ResNet (Residual Network): ResNet is a deep convolutional neural network architecture known for its ability to mitigate the vanishing gradient problem in deep networks. ResNet-based models have been effective in capturing intricate features within crack images.

Rsef: Residual Network with Feature Shrinking (Rsef) is a variant of ResNet that incorporates feature shrinking to reduce the computational complexity of the network. It has been used for efficient and accurate crack detection.

Ensemble Learning: Ensemble learning techniques, such as combining predictions from multiple models, have been employed to enhance crack detection accuracy and robustness, demonstrating improved performance over individual models.

CrackNet: CrackNet is a specialized architecture designed explicitly for crack detection. It employs convolutional and pooling layers to capture crack patterns and structural features, resulting in high accuracy.

Mask RCNN and Fast RCNN: These architectures extend CNNs to perform instance segmentation, enabling accurate identification and localization of individual cracks within images.

Inceptionv3, IterLUNet, VGG, MobileNet, Xception, GoogleNet, ShuffleNet, and Omni-Dimensional Dynamic Convolution: These deep learning architectures have been explored to optimize feature extraction and crack detection performance, leveraging their unique design principles.

Pixel-intensity resemblance measurement (PIRM), CTCD-Net, and DeepLab: Specialized techniques have been developed to assess pixel-level resemblance and semantic segmentation, allowing for detailed and fine-grained crack detection.

Adversarial Network and STRNet: Adversarial networks and architecture variants like STRNet have been used to enhance model robustness and generalization, contributing to more reliable crack detection. In Table 6 we can see the main methods which mentioned above, with the papers that they use them. The comprehensive details and utilization of these algorithms in the surveyed papers can be found in Table 7 providing valuable insights into their specific applications and performance in crack detection tasks.

# 3 Results and discussion

## 3.1 Results

The “Results” section of a crack detection study is a critical component that showcases the performance and effectiveness of the proposed methodologies. It provides a quantitative assessment of how well the developed algorithms and models perform in detecting and classifying cracks in various structures. This section serves as a validation of the proposed solutions, allowing researchers to evaluate their contributions and compare them to existing methods.

## 3.2 Metrics for evaluating results

To objectively evaluate the performance of crack detection algorithms, researchers employ a variety of metrics that assess different aspects of model performance. These metrics provide insights into the accuracy, precision, recall, and overall effectiveness of the methods. Let’s explore some of the commonly used metrics in crack detection research:

Accuracy: Accuracy measures the proportion of correctly predicted crack and non-crack instances among all predictions. It provides an overall assessment of the model’s correctness but might be skewed in imbalanced datasets.

Precision: Precision determines the proportion of accurate positive forecasts to all instances of positive predictions. It indicates the model’s ability to correctly identify positive cases, minimizing false positives.

Recall (Sensitivity): The ratio of accurate positive predictions to all actual positive cases is calculated using recall. It highlights the model's capacity to identify all positive cases, minimizing false negatives.

F1 Score: The harmonic mean of recall and precision is the F1 score. It balances the trade-off between precision and recall, providing a single metric to assess the model's performance.

Intersection over Union (IoU): IoU calculates how much of the expected and actual bounding boxes or masks overlap. It is commonly used in object detection and segmentation tasks.

Mean Average Precision (mAP): The average precision across various confidence threshold levels is determined by mAP. It is often used in object detection tasks to evaluate the precision-recall curve.

Receiver Operating Characteristic (ROC) Curve: The true positive rate *versus* the false positive rate at different categorization criteria are plotted on the ROC curve. A popular statistic used to evaluate the effectiveness of models is the area under the ROC curve (AUC-ROC).

Precision-Recall (PR) Curve: The PR curve illustrates the trade-off between the two metrics by plotting recall against precision at various categorization levels.

Dice Coefficient: The Dice coefficient measures the similarity between the predicted and ground truth segmentation masks.

Matthews Correlation Coefficient (MCC): MCC offers a balanced statistic for binary classification tasks by accounting for true positive, true negative, false positive, and false negative predictions.

These metrics collectively offer a comprehensive view of a crack detection model's performance. Researchers select the appropriate metrics based on the specific objectives of their study and the nature of the crack detection problem.

Supplementary Table S1 presents a detailed overview of the results obtained from the 85 reviewed papers. The table offers insights into the performance of various crack detection algorithms across different metrics, providing a comprehensive analysis of their effectiveness in real-world scenarios. The subsequent sections delve into the specific findings and trends observed in the evaluated papers, shedding light on the advancements and challenges in crack detection technologies.

## 3.3 Discussion

The field of crack detection has witnessed significant advancements owing to the integration of deep learning techniques. In this discussion, we delve into the collective insights, contributions, and limitations presented across a diverse range of recent research papers. As we navigate through the reviewed studies, we categorize them based on their innovative approaches and the identified gaps or limitations.

The introduction of the "Custom YOLOv7" model by Ashraf et al. (2023) marks a substantial stride in crack detection. This model achieves exceptional accuracy on both the RDD2022 dataset and a custom dataset. While the model's performance is remarkable, opportunities lie in refining its efficiency and exploring pixel-level segmentation strategies. Yang et al. (2023)'s "AttentionCrack" network presents a promising solution to enhance crack detection accuracy by addressing inaccuracies in boundary localization. The model demonstrates impressive F1 scores on benchmark datasets. However, the authors highlight potential areas of exploration, such as attention mechanisms and dilated convolution modules, to further enhance performance. Kim Y. et al. (2023)'s "Rsef-Edge," built upon the U-net architecture, stands out for achieving an accuracy rate of 97.36%. The paper suggests the implementation of an edge computing-based crack detection system. Nevertheless, challenges and potential advantages related to distributed deep learning form an essential part of the ongoing discussion. The "Stacking Ensemble Model" proposed by Lee et al. (2023) offers a novel approach to crack segmentation by leveraging ensemble learning. This model achieves an Intersection over Union (IoU) of 0.74, significantly outperforming FCN-8s. The focus on stacking ensemble learning and its impact on performance opens avenues for further investigation. Zhang J. et al. (2023)'s "Automated Yolo v4" introduces a method that emphasizes precision, recall, and F1 scores, showcasing a compelling alternative to existing approaches. The paper highlights the model's efficiency and compactness, making it a viable solution. However, addressing the challenges posed by imbalanced data remains a crucial direction for future research.

In "CrackNet" and "CrackClassification," Zhao Y. et al. (2023) contribute with their novel CrackNet model and CrackClassification algorithm. The study reports average precision (AP) scores for the CrackNet network across various datasets. The insights from this work shed light on the potential of the proposed methods in the context of crack detection. Maslan and Cicmanec (2023) propose the utilization of Yolo v2 for crack detection, resulting in an average precision (AP) of 0.89. This work showcases the model's competency in crack detection and sets the stage for discussions on the selection of YOLO versions for optimal results. Lv et al. (2023)'s "Mask R-CNN" presents a robust solution based on the mask region-based Convolutional Neural Network. The model achieves accuracy rates ranging from 95% to 99% on diverse datasets. While the model's performance is commendable, the paper also acknowledges the need for thorough comparative analysis and the selection of pooling layers. Wang (2023)'s "CrackSN" system, built on the Adam-SqueezeNet architecture, achieves an accuracy of 97.3% in classifying cracked patches. The authors discuss the positive aspects and limitations of their system, including its reliance on specific datasets and the potential for improving pixel-level accuracy. The novel proposal of "EfficientNet with Residual U-Net" by Gooda et al. (2023) combines segmentation and detection techniques to achieve an impressive accuracy of 99.35%. The paper's methodology and results provide a strong foundation for further exploration, while the discussion raises questions about computational requirements and improvements in the proposed methods. Kapadia et al. (2023)'s work on the "Inceptionv3" model adds valuable insights into accuracy, cross-entropy, precision, recall, and F-score values. The study acknowledges the challenges posed by acquired images and underlines the limitations of conventional algorithms in the domain of crack detection. Ngo et al. (2023)'s deep learning approach showcases an accuracy of 95.19% for crack detection. This work accentuates the importance of reliable datasets and addresses limitations in previous crack detection methods. The study's emphasis on dataset quality sets the stage for further investigation.

Chu et al. (2023)'s "Pothole Crack Detection (PCD)" model leverages a CNN-based approach to achieve remarkable precision and recall rates. The paper introduces a novel deep learning method that extends beyond crack detection to address road damage and pothole identification. The emphasis on decision support systems and a self-collected dataset enhances the practical relevance of the work. Bai et al. (2023)'s proposal to employ ResNet and ResNet + UNet for crack detection results in an accuracy of 67.6%. While the paper highlights the potential of these architectures, it also acknowledges the need for more labeled images and explores the utilization of benchmark datasets. The discussion reflects the ongoing pursuit of accurate and efficient crack detection solutions. Kolappan Geetha et al. (2023) take an innovative approach by employing an iterative differential sliding-window-based local image processing technique for missing crack detection. The study's focus on enhancing efficiency and introducing a novel scheme for eliminating missing shallow propagating crack segments offers new avenues for further research.

Inam et al. (2023)'s integration of YOLOv5 and U-Net for bridge crack detection demonstrates the potential of combining detection and segmentation approaches. This novel combination contributes to the field by showcasing the advantages of leveraging both models in tandem. The study also raises considerations for applying this approach to bridge crack detection in developing countries. Lee et al. (2023)'s "Image Processing and Deep Learning" method introduces a deep convolutional network (SSD) for object detection in tunnel images. The study compares various CNN models based on accuracy and discusses challenges in implementation and real-world feasibility. While the method holds promise, the paper acknowledges the need for more in-depth discussion on implementation challenges. Guo et al. (2023)'s adoption of a CNN (VGG16 + Focal Loss) for crack detection and quantification presents a promising way to estimate defect dimensions on complex structures. The paper's validation through gauge measurements and point cloud data opens avenues for applying the proposed approach to diverse scenarios. Li et al. (2023b)'s proposal of YOLOv7 with an attention mechanism for crack detection showcases improvements in precision and recall rates. The model's superior performance adds to the ongoing discourse on achieving a balance between accuracy and inference speed. Kim J.-Y. et al. (2023)'s "Blurred and Indistinct Concrete Crack Detection Framework" introduces a framework for detecting challenging blurred and indistinct concrete cracks. The paper explores the effectiveness of CNN models like AlexNet, VGG-16, and ResNet152 in classification and highlights the limitations of image filtering and thresholding methods. This work emphasizes the importance of tackling complex scenarios in crack detection. Tse et al. (2023)'s "Improved YOLOv4 with Attention Module" showcases an enhanced YOLOv4 model with an attention module that achieves high mean average precision (mAP). The study's focus on improving model efficiency and performance underscores the dynamic nature of crack detection research. Kao et al. (2023)'s "Combining YOLOv4 for Crack Detection" presents an approach utilizing YOLOv4 for accurate crack detection, validated through quantitative crack test methodologies. This work emphasizes the significance of image processing and edge detection techniques in achieving reliable results.

Lee and Yoo (2023)'s "Fast Encoder-Decoder Network with Scaling Attention" contributes a fast encoder-decoder network with scaling attention to the field. The model's competitive results and focus on detecting fine-grained cracks point towards the ongoing efforts to balance computational efficiency and precision. Zhao F. et al. (2023)'s "U-Net-Based Crack Segmentation with Morphological Network" introduces a novel crack segmentation method employing a U-Net-based architecture with a morphological network and multi-loss function. The proposed method's capability to improve crack segmentation performance under polarized light conditions adds a nuanced perspective to the field. Shim et al. (2023)'s "Stereo Adversarial Learning-Based Balanced Ensemble Discriminator Network" unveils a novel deep neural network with an adversarial learning-based balanced ensemble discriminator network. The model's performance in terms of intersection-over-union and F1 scores presents an intriguing avenue for addressing challenges posed by varying environmental conditions. Li et al. (2023a)'s "Intelligent Deep Learning for Crack Feature Extraction and Segmentation" introduces a two-stage transfer learning approach using ResNet50 and multilayer parallel residual attention (MPR) for crack feature extraction and segmentation. The study's emphasis on improvements over the benchmark UNet model underscores the potential of incorporating advanced neural network architectures. Popli et al. (2023)'s integration of a robot vision system with deep learning for road crack identification culminates in the identification of Xception as the most accurate and predictive model among the tested algorithms. The study's call for comprehensive investigations into crack detection complexities highlights the multifaceted nature of real-world applications. Xu et al. (2022)'s comparison of Fast RCNN, Mask RCNN, and YOLO for crack detection brings forth insights into the performance of these models. While Fast RCNN emerges with better results, this paper illustrates the importance of understanding the trade-offs between different detection architectures. Jayaraju et al. (2022)'s CNN-based approach for high-accuracy crack detection in building structures offers an efficient and objective solution. The paper's focus on utilizing a large dataset and CNN for precise detection draws attention to the potential of data-driven approaches in enhancing accuracy. Zhang et al. (2022)'s proposal for crack detection in earthen heritage sites using FPN-vgg16 combines effective crack extraction and transfer learning. The study's engagement with challenges related to deployment and uncertainty in crack attributes underscores the nuanced considerations in heritage preservation.

Wang et al. (2022b)'s "MA-Xnet" introduces an efficient mobile-attention X-network for crack detection. While the paper celebrates state-of-the-art performance and attention mechanisms, it acknowledges the need for further exploration in dataset generalization and computational complexity analysis. Li L. et al. (2022)'s utilization of Conv2D ResNet with an exponential activation layer yields superior results in wall defect classification. The study's call for further validation and assessment across different convolutional layers and loss functions underscores the iterative nature of deep learning research. Islam et al. (2022)'s "CNN-Based Transfer Learning for Crack Detection" introduces a transfer learning approach based on CNN for robust crack detection. The paper's demonstration of high accuracy across various deep learning models accentuates the importance of model selection in achieving reliable results. The need for diverse datasets and exploration of alternative neural network architectures remains open for further investigation. Ha et al. (2022)'s assessment of SqueezeNet, U-Net, and Mobilenet-SSD models for crack assessment highlights their high accuracy in defect classification. The paper's emphasis on accurate severity assessment and limitations involving depth information and system size draw attention to the complexity of evaluation metrics in real-world applications.

Loverdos and Sarhosis (2022)'s comparison of U-Net, DeepLabV3+, LinkNet (SM), and FPN (SM) models underscores their high accuracy in crack detection. The positive outcomes achieved by the block-detection model and crack detection model bring to light the significance of model selection and its impact on accuracy. Ali et al. (2022)'s vision-transformer (ViT) classifier for crack classification, localization, and segmentation reflects a promising integration of advanced algorithms. The high accuracy, precision, recall, and F1 scores achieved through this integration affirm the potential of combining state-of-the-art techniques. Wibowo et al. (2022)'s utilization of transfer learning with VGG16 and ResNet50, combined with ANN and kNN, in wall crack classification showcases a fusion of methodologies for enhanced accuracy. The paper's recognition of dataset quality and variety serves as a reminder of the fundamental role data plays in the efficacy of deep learning models. Pu et al. (2022)'s employment of a deep convolutional neural network (DCNN) with an encoder-decoder module for semantic segmentation and classification accentuates the significance of accuracy improvement. The promising outcomes demonstrated underscore the iterative nature of model enhancement and the potential of deep learning techniques. Munawar et al. (2022a)'s investigation into crack detection using a modified deep hierarchical CNN architecture and CycleGAN underscores the utility of guided filtering and CRFs for pixel-wise segmentation. The exploration of various accuracy metrics and techniques emphasizes the multifaceted nature of crack detection research. Ma J. et al. (2022)'s comparative evaluation of YOLO v3, YOLO v4s-mish, and YOLO v5s for crack detection in ancient timber structures provides insights into the strengths of different architectures. While YOLO v3 emerges as a strong performer, the study's focus on training speed speaks to the ongoing pursuit of efficient and accurate detection methods.

Wan et al. (2022)'s combination of SSD and an eight-neighborhood algorithm demonstrates high precision and recall in crack detection. The paper's recognition of challenges in length and width identification and its reference to specific scenarios highlight the diverse environments in which crack detection operates. Ren et al. (2022)'s utilization of YOLOv5 for precise pavement crack detection showcases advancements in model accuracy. The proposed method's ability to improve detection performance over existing methods reiterates the iterative nature of model development. Kang and Cha (2022)'s introduction of STRNet, a semantic transformer representation network, achieves high precision, recall, F1 score, and mIoU in crack segmentation. The paper's exploration of false positives and negatives underscores the complexities of segmenting intricate crack patterns. Siriborvornratanakul (2022)'s adoption of DeepLabV3-ResNet101 for damage detection addresses complex scene detection using deep learning solutions. The paper's identification of gaps in pixel-level localization highlights the need for holistic crack detection methodologies. Elghaish et al. (2022)'s development of a new CNN model that outperforms pre-trained models presents an exciting avenue for infrastructure maintenance. The call for ongoing investigations serves as a reminder of the evolving nature of crack detection research.

Wu et al. (2022)'s exploration of FCN architectures for crack detection showcases the ongoing pursuit of improving accuracy and handling complex crack patterns. The challenges posed by factors like illumination and the desire for precise part detection underscore the dynamic nature of detection techniques. Liu et al. (2022)'s incorporation of domain adaptation into DDACDN for crack detection highlights the model's high accuracy. The call for quantitative evaluation, active learning, and consideration of multi-scale objects acknowledges the intricacies of real-world implementation. Nomura et al. (2022)'s evaluation of YOLOv2 + VGG16 for damage detection emphasizes the importance of improving recall and addressing challenges related to over-detection. The paper's recognition of the need for automating detection processes aligns with the drive for efficiency in detection methodologies. Yu et al. (2022)'s contributions to intelligent performance improvements in DeepLabV3+ and YOLOv5 demonstrate the potential of these techniques in various contexts. The discussion of dataset scaling, new loss functions, and filtering methods invites further exploration and refinement. Munawar et al. (2022b)'s exploration of a CNN architecture coupled with CycleGAN for crack detection showcases the potential of guided filtering and offers insights into global accuracy, class average accuracy, intersection of union, precision, recall, and F-score metrics. The focus on CNN architecture and CycleGAN exemplifies the synergy between different techniques in enhancing crack detection. Kun et al. (2022)'s Deep Bridge Crack Classification (DBCC)-Net presents a unique approach by converting target detection from regression to binary classification. The paper's emphasis on achieving higher Miou while acknowledging limitations in reasoning time and available research data underscores the importance of innovative strategies. Mohammed et al. (2022)'s semi-supervised learning model for crack detection provides an avenue for reducing the need for labeled data while maintaining accuracy. The paper's alignment with efficient data utilization and training time optimization contributes to the ongoing exploration of deep learning techniques. Hammouch et al. (2022)'s comparative analysis of CNN and transfer learning models highlights the differential performance in detecting alligator cracks and longitudinal cracks. The paper's call for expanding longitudinal crack datasets underscores the significance of robust training data. Lee and Huh (2022)'s development of a mobile mapping system (MMS) for capturing real-time RGB and IR images of asphalt pavement surfaces showcases a fusion of sensor technology and deep learning. The paper's focus on diverse surface types and more expansive image data adds depth to the discussion of real-world applications. Lu et al. (2022)'s multi-scale crack detection network (MSCNet) with texture enhancement and feature aggregation demonstrates precision and recall rates. The paper's commitment to improving crack detection performance and inference speed aligns with the quest for accurate and efficient methodologies. Kim et al. (2022)'s Deep Bridge Crack Classification (DBCC)-Net introduces a novel approach with implications for improving Miou.

The study's recognition of limitations involving reasoning time and research data availability encourages ongoing exploration and validation.

As we conclude our journey through these papers, we embrace the diverse methodologies, insights, and advancements presented. From deep learning architectures and transfer learning to novel fusion techniques and real-world applications, this discussion underscores the multidimensional nature of crack detection research. As the field continues to evolve, these papers collectively provide a foundation for future exploration and innovation, inspiring researchers and practitioners to address challenges, bridge gaps, and strive for accurate and efficient crack detection solutions. To summarize this journey, we can say that the crack detection methodology described in the paper employs a diverse range of tools and techniques, primarily centered around deep learning algorithms and associated frameworks. These tools include.

1. Deep Learning Frameworks: The study utilizes various deep learning frameworks such as YOLO (You Only Look Once), UNet, ResNet (Residual Neural Network), Rsef, and others. These frameworks serve as the backbone for developing and training crack detection models, leveraging their capabilities in feature extraction, classification, and segmentation tasks.
2. Metrics and Evaluation Tools: To assess the performance of crack detection algorithms, the study employs a variety of metrics such as accuracy, precision, recall, F1 score, IoU (Intersection over Union), mAP (Mean Average Precision), ROC (Receiver Operating Characteristic) curve, PR (Precision-Recall) curve, Dice coefficient, and MCC (Matthews Correlation Coefficient). These metrics provide insights into the accuracy, robustness, and efficiency of the models.
3. Custom Model Implementations: The paper describes the development and implementation of custom models such as Custom YOLOv7, AttentionCrack, Rsef-Edge, Stacking Ensemble Model, Automated YOLO v4, CrackNet, CrackClassification, Mask R-CNN, EfficientNet with Residual U-Net, and others. These custom models incorporate novel architectures, attention mechanisms, and ensemble learning techniques to enhance crack detection accuracy and efficiency.
4. Data Processing and Annotation Tools: In addition to deep learning frameworks, the study may utilize various data processing and annotation tools for preprocessing raw data, labeling crack instances, and augmenting datasets. These tools ensure the quality and diversity of the training data, contributing to the robustness of the crack detection models.
5. Model Training and Optimization Tools: Model training and optimization are critical components of the crack detection methodology, requiring tools for hyperparameter tuning, optimization algorithms, and training pipelines. These tools help fine-tune model parameters, improve convergence speed, and enhance overall performance.

In summary, the crack detection methodology outlined in the paper leverages a combination of deep learning frameworks, evaluation metrics, custom model implementations, data processing tools, and model training techniques to achieve accurate and efficient crack detection results. These tools collectively enable researchers to develop, evaluate, and optimize crack detection algorithms for various real-world applications.

# 4 Conclusion

In this comprehensive survey paper, we embarked on a journey through the landscape of crack detection methodologies, datasets, algorithms, and results. The evolution of crack detection technologies has been remarkable, driven by the integration of cutting-edge machine learning and deep learning techniques. Our exploration revealed a diverse array of strategies, methodologies, and advancements that collectively contribute to the enhancement of structural health assessment.

As we traversed through the realms of crack detection, it became evident that traditional approaches have taken a backseat in favor of innovative and state-of-the-art methods. A prevailing trend among the surveyed articles was the utilization of contemporary variants of algorithms, such as the latest versions of YOLO, UNet, ResNet, Rsef, and more. This signifies a dynamic shift towards harnessing the full potential of modern techniques to address the complex challenges of crack detection.

A striking observation in this survey was the prevalent use of multiple algorithms within a single study. Many researchers adopted a holistic approach by combining various algorithms, with one focused on crack detection and another dedicated to segmentation. This synergy enables a more comprehensive analysis, leveraging the strengths of different methods to achieve more accurate and robust results.

Furthermore, several papers demonstrated ingenuity by devising hybrid architectures that amalgamate basic and expert models. This innovative approach capitalizes on the strengths of each model type, potentially yielding enhanced performance and adaptability in crack detection scenarios.

Authors across various papers showcased a penchant for pioneering methods and technologies in both data collection and algorithm development. This inventive spirit has led to the construction of novel datasets, precise annotations, and ingenious models tailored to the intricacies of real-world crack detection challenges.

As we peer into the future, the survey highlights the potential for further exploration and innovation. Emerging technologies like Vision Transformers (ViT) hold promise in the realm of crack detection, offering new avenues for enhancing model performance and adaptability. The integration of ViT and other groundbreaking algorithms presents exciting opportunities for researchers to push the boundaries of crack detection capabilities.

In conclusion, the amalgamation of advanced algorithms, diverse datasets, and pioneering methodologies showcased in this survey underscores the dynamic nature of crack detection research. The journey through the diverse facets of this field not only offers a deeper understanding of its current state but also inspires new horizons of exploration. As the cracks in our built environment continue to challenge us, this survey paper serves as a roadmap for researchers and practitioners, guiding them towards the next era of innovation and excellence in crack detection technologies.

## Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

## Author contributions

HK: Conceptualization, Investigation, Writing–original draft, Writing–review and editing. RA: Conceptualization, Investigation, Supervision, Writing–review and editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fbuil.2024.1321634/full#supplementary-material

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