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CURRENT LITERATURE REVIEW ON IMAGE PROCESSING ANALYSIS FOR CONCRETE DAMAGE ASSESMENT

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Abstract

Numerous studies have employed computer vision algorithms to analyze images of concrete damage. Therefore, conducting an image processing survey to detect concrete damage is very crucial. Thus, an image processing algorithm analysis survey to detect concrete damage was conducted using various algorithms and types of data from the last decade. The data observed were the first is damage to concrete, which included surface cracks, hairlines, crack width, patterns, holes, diagonal cracks, longitudinal cracks, and transverse cracks. The second part is figuring out where roads, bridges, and buildings are. The third is data sources like digital cameras, cameras built into phones, camera sensor systems, and unmanned aerial vehicles (UAVs). The study's findings indicate that image processing algorithms will play an essential role in future assessment research on the automation of concrete damage detection. This is particularly the case in high-risk regions for security reasons, and UAV technology is required to reach these locations.

Keywords: Computer Vision, Concrete Damage, Image Processing

Introduction

The need for construction and infrastructure development is rising with economic growth and development. Concrete structures are among the most often utilized building materials (Dinakar et al., 2013). Because concrete has high compressive strength and outstanding adaptability and durability in all weather conditions, it is widely applied for all types of construction (Pimienta et al., 2017) (D. Zheng et al., 2020). In addition to some of its benefits, concrete also has a disadvantage; mainly, it is poor at enduring tension, requiring reinforcing steel. Furthermore, cracks in concrete can result from bending, shear, and torsion, as well as shrinkage produced by the hydraulic characteristics of cement (Ouypornprasert et al., 2018) (Gastaldi et al., 2011).

Concrete cracks indicate the beginning of degradation; once the cracks emerge, the reinforcing steel will oxidize (Holland et al., 2016). Early diagnosis of concrete cracks is crucial to preventing more severe damage and keeping the structural elements suitable for service load conditions (Hillerborg et al., 1976).

Both structural and non-structural cracks can exist in concrete. The size of the crack gap demands a more significant positive than the total number of cracks in structural cracks (Sohn et al., 2005). Therefore, having numerous hair cracks is preferable to having a couple with many substantial gaps. The longitudinal direction of the reinforcement and lateral loads will be present in reinforced concrete structures toward the tensile reinforcement. The tensile zone contains lateral strains in the bond of concrete and reinforcing steel when the longitudinal stress-strain curve develops in the structural member before cracking in the concrete. Since the longitudinal tensile stress of the concrete in that area is likewise lost when concrete begins to crack, the cracked component of the biaxial force is lost (Swaddiwudhipong et al., 2003).

Additionally, the longitudinal bonding strength between the concrete and the reinforcement keeps growing until it reaches its maximum at the particular crack zone, which further results in the concrete conducting the highest strain. An early failure occurs when the concrete damage begins to crack (X. Wang, 2012).

Early diagnosis of these cracks during the inspection is crucial to reducing structural failure caused by concrete cracks (Mohan & Poobal, 2018). Now it is possible to evaluate concrete cracks mechanically rather than by hand. Automatic crack inspection may reduce errors or problems while also speeding up work. Unmanned aerial vehicles (UAV), deep learning image processing using a variety of convolutional neural network (CNN) and Fully Convolutional Network (FCN) algorithms, such as U-Net, VGG-16, and VGG-19, traditional image processing using Canny edge detection, Sobel edge detection, SHIFT, etc., and image processing model optimization algorithms using Generative Adversarial Networks (GAN) and Genetic Programming (GP) can all be used to perform the automatic concrete crack inspection (Valença et al., 2017) (An et al., 2022).

Building inspections and maintenance must be carried out regularly, and crack detection is a core component of the inspection process. Traditional inspection procedures are time-consuming and risk falling from a height. UAVs with computer vision technology can solve this problem in the visual inspection of cracks in concrete (Y. Liu et al., 2020). Image deterioration in the form of motion blur brought on by the UAV during photography is one of the difficulties in automated crack inspection visualization. Motion blur is caused by the UAV platform's high vibration, which might make fracture identification difficult. The high link between blurred cracks and clear photos was identified using a deep learning-based deblurring model based on GAN. Experimental validation of the proposed deblurring model was conducted to determine how residual connections affect deblurring. The result showed that the proposed model could significantly improve global structure deblurring performance and feature detail in images of cracked concrete compared with the advanced deblurring model. The GAN method is used for crack identification and can handle fuzzy images. The UAV's crack detection images create extremely detailed visualizations that might show the concrete's porosity (Y. Liu et al., 2020).

Using CNN ResNet 101 image segmentation, a concrete crack inspection is performed. Use Labelme software to label the dataset, followed by a deep learning framework to train the network model better. The process of feature extraction is fundamental. The FCN algorithm is matched with the CNN ResNet 101 method. Image segmentation utilizes a confusion matrix with accuracy and recall to assess the classification outcomes. False Positive (FP) is the indicator of pixels predicted to crack incorrectly, and True Positive (TP) denotes the number of pixels predicted to crack correctly. False Negative (FN) denotes the number of pixels predicted not to crack. Image segmentation for CNN ResNet 101 crack identification leads to more excellent performance and accuracy, whereas FCN image segmentation causes noise and lacks information for crack detection. Concrete crack detection accuracy may be improved by using CNN ResNet 101 image segmentation model since it has a straightforward structure, high scalability, and effective segmentation (Meng, 2021).

Applying image processing methods to camera images with variable damage, position, potential damage, crack length, width, and depth. Two popular techniques with advantages and disadvantages are targeting and image processing. The image processing method locates the crack precisely on many surfaces. However, the results of the detection might still contain inaccuracies. This error may be eliminated by recent technological advancements such as Wavelet transform (WT) and mathematical equations such as Digital Image Correlation (DIC). Detect concrete defects in crucial locations, such as corners, by combining the super vector machine (SVM) algorithm with CNN-based image processing methods and Deep learning with VGG-Net (Hosseinzadeh et al., 2020).

Concrete crack detection may be accomplished using conventional image processing techniques, including Prewitt, Sobel, Gaussian, Roberts, Canny, and Laplacian corner detection. Corner detection is performed using a Laplacian filter in the Butterworth frequency domain. The Sobel edge detector discovers more edges and dynamic computations than the canny edge detector when both algorithms are compared to identify concrete cracks. However, a fit detector creates more inaccuracy detection. Prewitt and Robert's detectors identified a variety of edges, but they were not good at locating small edges with false thresholds. Noise reduction and wrong edge detection location in the image are drawbacks of all gradient-based edge detectors. The noise can be minimized, but the edge detection location worsens as the kernel size increases. Images with sharp intensity changes and noise are excellent for edge detection-based second-order derivatives (Andrushia et al., 2018).

Conventional and deep learning-based image processing are considered in the paper's criteria for image processing in the context of the concrete crack. Every article assessed will consider the status of critical thinking according to the results of the papers examined, and each paper overviewed will check for biases in the research papers from the survey. Chapter 2 (Methodology), which details the entire survey process in Figure 1 in the form of a flow chart, then follows further to discuss the validation procedure, data extraction, and data synthesis, and the methodology by using the article as a reference for the survey will be described. The different image processing techniques, ranging from conventional to deep learning-based, are described in Chapter 3. In Chapter 3 the architecture of image processing is discussed. Chapter 4 discusses current trends in the use of image processing for the identification of concrete defects. The conclusion and implications for image processing's use in identifying damage to concrete come last in Chapter 5.

Research Methodology

In this survey, each step of the study will result in an important discovery in image processing, particularly concerning the detection of concrete defects. The study may be divided into various components using the flow chart shown in Figure 1.

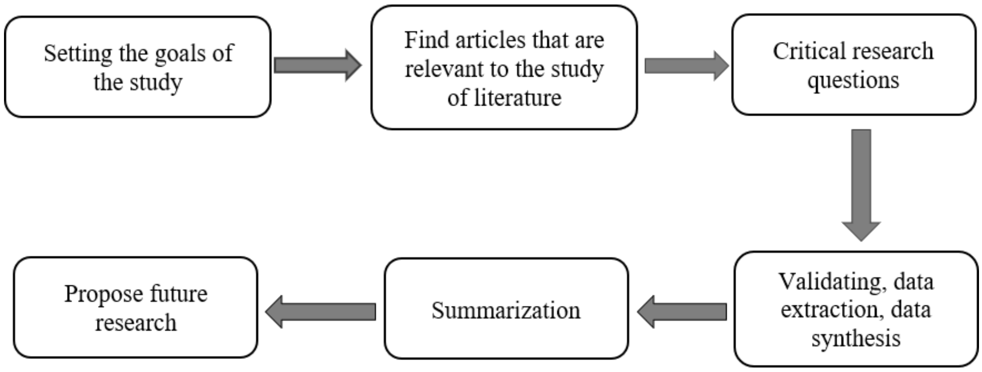

Figure 1. Flow chart survey state-of-the-art concrete crack detection

1. **Validating Procedure**
   The examined articles are presented in the publications category that Scopus and the Web of Science have indexed. These papers come from various sources, including the ASCE journal, the Elsevier group, Springer, and other publishers. This goal is to keep the survey outcomes quality excellent. It is necessary to identify research relevant to the identification of concrete cracks to restrict the scope of the study, particularly addressing image processing methods, including those that are conventional and those that are based on deep learning. The analyzed publications were published between 2012 and 2022 and dealt with image-processing applications to concrete crack identification.
2. **Data Extraction**
   The selected articles are from credible journal publications. They are organized according to the number of citations, research topics, and developments using image-processing algorithms to detect concrete cracks. Important discoveries made in image processing will be discussed and brought to light to be presented as potential research topics shortly.
3. **Data Synthesis**
   The information gathered will be presented in tables and bar charts making it easier for researchers to continue their work in image processing, particularly when spotting cracks in concrete

Research Results

1. **Image processing in concrete defect**
   A step known as data augmentation occurs first, before the phases of image processing and image segmentation, respectively. It is required to pass through a data augmentation system to be used by CNN for training. This system may be implemented in different methods, including flipping, color rotation, random cropping, and random combining (Khan et al., 2018).
   Traditional image processing techniques and deep learning can be used in the image processing processes used to identify cracks in concrete (Wenshuo Gao et al., 2010). Image processing methods may also be used. The collected photographs are analyzed and categorized by the degree of the crack, such as whether it is a structural crack or simply a surface crack. These images serve as training data. After that, the data from the test are used to validate the data from the training. Traditional techniques such as canny, Sobel edge detection, and others can greatly assist when processing images on photographs that include concrete cracks. In addition, techniques for processing images based on deep learning, such as U-Net, FCN, VGG, and others, are highly beneficial (Ji et al., 2018).

A. Traditional image processing

Edge detection is a term that's often used when referring to traditional image processing. The process of calculating edge regions in an image with varying depths requires a technique called edge detection. The estimated area organizes itself into a matrix, resulting in a discernible distinction between the edge areas, indicating the presence of an edge. The Sobel edge detection method, the canny edge detection algorithm, the Roberts algorithm, and the Prewitt algorithm are all well-known examples of edge detection algorithms.

Equation (1) may be used to construct the implementation of the convolution kernels pixel the matrix operator on Sobel edge detection (J. Wang et al., 2021).

$$Ex = [+1\ 0\ -1\ +2\ 0\ -2\ +1\ 0\ -1\ ],\ Ey = [+1\ +2\ +1\ 0\ 0\ 0\ -1\ -2\ -1\ ] \quad (1)$$

According to Equation (2), the Prewitt edge detection technique similarly uses convolutional kernels matrix 3x3, making it identical to the Sobel edge detection algorithm (J. Wang et al., 2021).

$$Ex = [-1\ 0\ +1\ -1\ 0\ +1\ -1\ 0\ +1\ ],\ Ey = [-1\ -1\ -1\ 0\ 0\ 0\ +1\ +1\ +1\ ] \quad (2)$$

B. Deep Learning Base Image Processing

FCN is one of the image processing techniques based on deep learning that is used most frequently. Image processing in FCN consists of many more layers and parameters than in other systems. FCN object detection brings crack detection down the level of the image to the level of the pixel, such that image processing enables the pixel in the image to be recognized by the lens of the target object. Cracks may be found and measured with high precision using pixel-level detection due to their unique capabilities. Because of this, FCN can identify and analyze cracks at various pixel levels even when there are many cracks (X. Yang et al., 2018). Each data layer that makes up the FCN is a three-dimensional array with the dimensions h, w, and d. Where h and w refer to the spatial dimensions and d refers to the size of the feature or channel. The image is the first layer, its pixel dimensions are h by w, and its color channel is d. The location of the top layer matches the location of the image linked by the convolution layer (Long et al., 2017):

FCN uses CNN to extract the image feature model.

A convolution layer is used to transform the number of channels into the number of classes.

A transposed convolution layer is used to modify the pixel height and width to match those in the input image.

Up sampling using bilinear interpolation is a method that may be used before beginning the convolutional layer translation process in the FCN. "Convolutional" refers to an operation that performs some addition, integration, multiplication, or derivation on two separate data sets. Equation (3) is used as the convolution below (Islam & Kim, 2019).

$$y = s * w ==> y[i] = \sum_{j=-a}^{+a} s[i-j]w[j] \quad (3)$$

Where s represents the data fed into a convolutional filter, and w refers to the kernel used. The feature model may be constructed using Equation 3 by executing a convolution operation and then applying the kernel to all the inputs.

U-net is an example of a forwarding control network. U-Net is a network used for semantic segmentation, which categorizes pixels of an image so that they belong to the same class. It gets the name from the network, which is a "U," and this shape can be seen in the picture that can be found in figure 2.

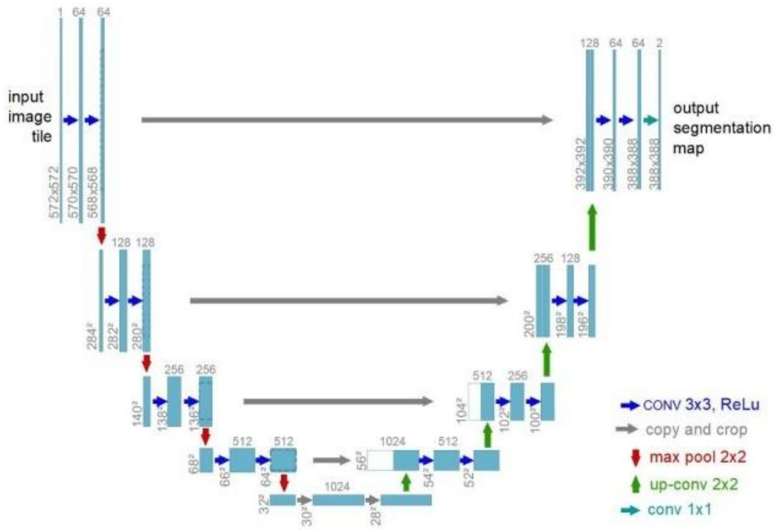

Figure 2 U-Net architecture (Ronneberger et al., 2015).

Only one convolutional layer was employed in the first version of the LeNet CNN that was successfully developed, followed by a pooling layer. Yann LeCun is credited with being the one who initially implemented LeNet in the 1990s for use in applications involving handwriting recognition (El-Sawy et al., 2017).

The AlexNet CNN architecture is one of the most widely used in computer vision (Almisreb et al., 2018). Eight weighting classes are included in AlexNet, and they are made up of five convolution layers and three FCN layers. Except for the very final layer, which generates a SoftMax with a distribution of more than one thousand class labels, the ReLu activation procedure is carried out after every layer. The first two layers of the FCN are subjected to the bulk of the weighing applied (Sellami & Tabbone, 2021). In detecting cracks in concrete using AlexNet, the concrete crack images are fed directly into the classification model. This step is very helpful for users since it will save much computing time without sacrificing accuracy.

The research conducted by Visual Geometry Group (VGGNet) demonstrates that having a deep network is essential in producing high performance. Using VGGNet for image processing yields a CNN network with a high degree of precision. According to Simonian and Zisserman (2014), the best VGGNet network has 16 convolutional fully connected layers, a homogeneous architecture, and only performs 3x3 convolution and 2x2 pooling from the beginning to the end. This type of network also has a homogeneous architecture. VGGNet's computation time is rather lengthy since it uses many parameters until it reaches 140 million, most of which are entirely linked layers at the beginning (Simonyan & Zisserman, 2015). It causes the computation time for VGGNet to be relatively longer.

The error rate increases and the accuracy decreases if one network gets too deep, which causes the vanishing gradient issue. ResNet has benefits over other image processing methods, one of which is that the error rate increases. The vanishing gradient issue will be solved using ResNet by skipping and moving through several layers, a process that is sometimes referred to as residual learning. The ResNet design addresses the issue of disappearing gradients by including skip connections, using batch normalization, and doing away with the fully connected layer located at the very end (Meng, 2021).

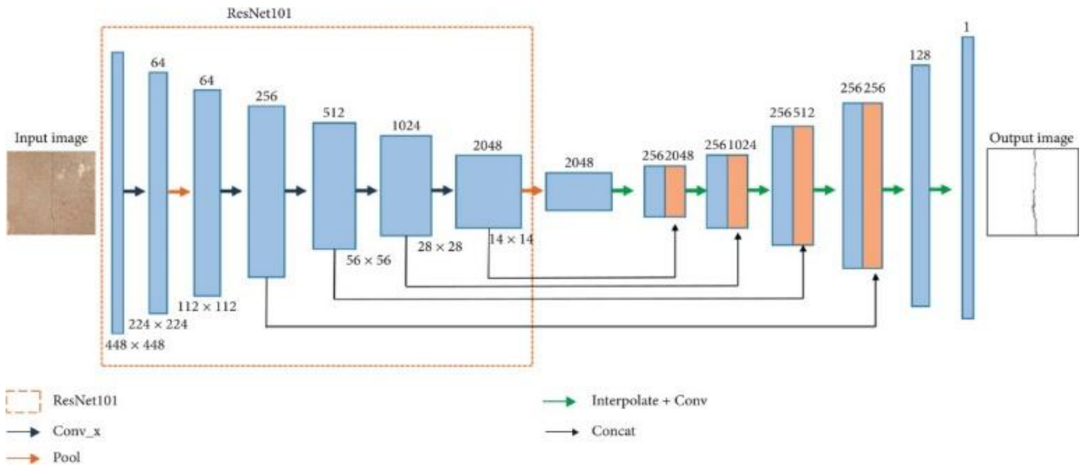

Figure 3 The architecture of ResNet in concrete crack detection (Meng, 2021).

GoogleNet develops the Inception Module, which brings the total number of CNN parameters down from 4 million to a more manageable level. The number of AlexNet parameters that exceed 60 million is far more than this statistic, which is substantially lower. In contrast to other CNN designs, which use a fully connected layer at the very top, GoogleNet uses average pooling at the very top to eliminate many parameters that are not very significant (Szegedy et al., 2014).

C. UAV

UAVs are a category of aircraft capable of flight without the presence of a human pilot. UAVs comprise a ground control station, a collection of sensors, and an airplane component. Operating UAVs can either be by electronic equipment on board or on the ground (Watts et al., 2012).

The evolution of UAV technology has seen widespread use across many different industries. For instance, using UAVs equipped with computer vision allows for capturing photos from a greater distance, which is utilized for 3D mapping of mining project surveys. In this article, the contrast calculation of Robotic Total Station (RTS) estimates was made manually with the support of UAV technologies results of the UAV proved superior to the experiment with RTS, as the results of a comparison of measurements RTS. There are distinct variations in the outcomes of the RTS conducted with the UAV based on the three experimental settings. There is a difference of 8% between Experiment I and Experiment II, 9% between Experiment II and Experiment III, and 16% between Experiment III and itself. The difference between the three heaps in the total amount of dirt assessed is between 8 and 16%. It is considered that the measurements obtained from the UAV offer a more accurate estimate of the volume of the earth (Siebert & Teizer, 2014). This is because the RTS captures fewer locations

Discussion

1. Trend image processing in concrete defect inspection

Image processing based on deep learning CNN VGGNet with an SVM model was built by Hosseinzadeh et al. (2020) to identify cracks in concrete. Crack image collections may be recovered from various challenging angles, even at confluence angles of 90 degrees. The confusion matrix and recall techniques are used to evaluate the effectiveness of classification, and the resultant accuracy rate is 93%. The FCN-AlexNet technique was used by Yang et al. (2018) to study the detection of concrete defects utilizing 10 neuronal connections. The accuracy of evaluating the combination of the K-Fold Validation and Confusion Matrix method with the F1-Score method and the precision method is high after being assessed by various methods, including the K-fold validation and confusion matrix method with an accuracy of 96%. If the training dataset is less than the test dataset, then the model is more likely to overfit and take longer to converge. It results in a drop in accuracy. M. Zheng et al. (2020) conducted a study by comparing 3 convolutional neural network models, namely FCN (Fully Convolutional Network), R-CNN (Regions-Convolutional Network), and RFCN (Richer Fully Convolutional Network), to detect cracks in concrete. The dataset consists of 5000 images containing crack images on roads, bridges, houses, and dams. The evaluation process uses the Confusion Matrix and produces the highest accuracy, namely RFCN, which reaches 98%, and the average accuracy of the three models is 87%. The FCN model has shortcomings in detecting angles in the image. However, the RFCN model, a combination of the FCN model with RFN, which can detect the angle of an image, is effective in increasing the accuracy of the FCN model. However, suppose the dataset has a problem with inconsistent images within a specific range. The RFCN Model will increase accuracy and slow detection due to a longer training process.

Qu et al. (2020) examined the detection of concrete cracks on pavements divided into 2 parts, namely the classification of fine-tuned LeNet-5 crack models and crack detection using the VGG16 model. The LeNet-5 model helps classify the original image, whether a crack, fake crack, artificial scratch, entire surface, or vegetation. At this step, the image must be normalized before input to the neural network and combined with pre- processing software with a standard notion of 256 x 256 pixels. The output dimensions of the LeNet-5 FD2 layer have been modified and get the highest accuracy of 95% on the crack data. The next step is crack detection using the VGG16, U-Net, Percolation, and VGG16 Modified models. In this study, VGG16 Updated has been modified in some ways, including removing Conv1, Conv2, and Conv6 from the original VGG16 model. It improved detection efficiency by extracting only helpful features using several parameters. In addition, the horizontal expansion technique, the convolution kernel, and the use of a two-layer link from the up-sampling layer are the distinguishing characteristics that constitute this distinction. The evaluation approach uses a cross-entropy loss function, and the findings of the modified VGG16 model reveal that the F1 score may reach 0.896 when applied to the CFD dataset. Compared to VGG16, U-Net, and Percolation, there was an increase of 25.2%, 2.8%, and 39.1%, respectively, compared to the three models. The F1 score comes in at 0.892 for the dataset known as Cracktree200. Compared to VGG16, U-Net, and Percolation, there was an increase of 50.3%, 16.6%, and 68.9%, respectively, compared to the three models. After then, the F1 score for the Deep Crack dataset achieved 0.901. There was an increase of 53% when compared to VGG16, 5.2% when compared to U-Net, and 52.2% when compared to Percolation compared to the three models. Hoang and Nguyen (2018) can automatically and swiftly locate cracks in concrete walls using digital camera capture. The newly created model known as MO-EDCR uses four distinct approaches to edge detection. These are known as the Roberts, Prewitt, Sobel, and Canny approaches. According to the findings of the tests, the Prewitt algorithm performs the best. It has a Classification Accuracy Rate (CAR) of 89.954% and an area under the curve (AUC) of 0.9. Kim et al. (2015) apply encapsulated UAV technology to detect crack widths calculated using image processing with crack widths measured using crack gauges. The UAV is equipped with a Raspberry Pi, camera, and ultrasonic displacement sensor, which can measure crack images and related distance information while the UAV is flying. Cracked images taken using UAV are processed using Image segmentation. Then using the Sauvola Method corrects the grayscale image to black and white used to reduce noise. The next step is to compare the results of the crack segmentation from the image by applying the technique for assessing crack width, where each pixel in the frame and the relevant edge pixel are used. A validation test was conducted on concrete walls with cracks of varying lengths, widths, and patterns. The area examined is about 1.5 m above the ground. The actual crack information is used as a reference to compare with the calculated crack width. From the field experiment, the computed crack width is the same as that measured by a crack gauge, as shown in Table 1.

Table 1. Actual Crack Width and Image Processing Crack Width (KIM ET AL., 2015)

NO	Position	Image Processing	Actual
1	A	0.36	0.35
2	B	0.25	0.25

Table 2 presents a few methods that have been used in mapping the trend of image processing research in detecting defects in concrete over the last ten years.

Table 2. A Recent Trend in Image Processing for Concrete Defect Detection

NO	Author	Image Processing	Data Source	Dataset	Defect Category	Object
1	Detchev et al. 2012)	Edge detection: Roberts, Sobel, Prewitt, Canny	Fiber optic sensor camera	-	Crack width	Concrete beam
2	Zou et al. (2012)	Automatic crack detection: Crack Tree	High-speed camera	206 images	Shape crack	Concrete pavement
3	Xu and Zhang (2013)	Edge detection: Roberts, Sobel, Prewitt, Canny, G_Laplacian	Video camera	15 images	Crack width	Concrete bridges
4	Rabah et al. (2013)	Automatic crack detection: shading correction, crack mapping, and processing	TLS: Terrestrial Laser Scanner	230 images	Surface crack	-
5	Nguyen et al. (2014)	Edge detection: Savitzky-Golar filter	-	-	Crack width	Concrete building
6	Liu et al. (2016)	SIFT: Scale Invariant Feature Transform	Digital camera	-	Deep crack	Concrete wall
7	Oliveira and Correia (2014)	Automatic crack detection: Crack IT	Optical device	84 images	Longitudinal and transversal crack	Concrete pavement
8	Amhaz et al. (2014)	Automatic crack detection: Minimum path selection	Mobile camera	36 grey images	Crack pattern	Concrete pavement

NO	Author	Image Processing	Data Source	Dataset	Defect Category	Object
9	Yang et al. (2015)	Impro stereo	Remote camera	-	Deflection	Concrete bridges
10	Dinh et al. (2016)	Image binarization: Sauvola method	Robotic camera	-	Surface crack	-
11	Amhaz et al. (2016)	Automatic crack detection: Minimum path selection	Mobile camera	269 images	Crack pattern	Concrete pavement
12	Kim et al. (2017)	Image binarization: Sauvola method	UAV	20 images	Surface crack	Concrete wall
13	Li et al. (2017)	Edge detection: Canny	Digital camera	1200 images	Crack width	Concrete bridges
14	Cho et al. (2018)	Image binarization: Otsu method	TLS	-	Crack width	Concrete wall
15	Kang and Cha (2018)	CNN	Digital camera	100 videos	Crack width	Concrete building
16	Yusof et al. (2018)	DCNN	Digital camera	7000 images	Crack width	Concrete pavement
17	Andrushia et al. (2018)	Edge detection: Canny, Roberts, Prewitt, Sobel	-	-	Crack width	Concrete bridges
18	Hoang (2018)	Image binarization: Otsu method	Digital camera	-	Crack width	Concrete pavement
19	Yang et al. (2018)	AlexNet	Digital camera	800 images	Crack pattern	Concrete pavement
20	Hoang and Nguyen (2018)	Edge detection: Roberts, Canny, Prewitt, Sobel	Smartphone camera	1620 images	Thin crack	Concrete wall
21	Yang et al. (2018)	FCN	Digital camera	800 images	Void, pits, and leakage	Concrete wall
22	Islam and Kim (2019)	FCN and VGGNet	Digital camera	40000 images	Crack width	Concrete bridges
23	Liu et al. (2019)	U-Net	Digital camera	500 images	Crack width	Concrete bridges

NO	Author	Image Processing	Data Source	Dataset	Defect Category	Object
24	Li and Zhao (2019)	DCNN	Smartphone camera	1455 images	Crack width	-
25	Zheng et al. (2020)	FCN, RFCN, RCNN	Digital camera	5000 images	Surface crack	Concrete bridges, buildings, and dams
26	Ren et al. (2020)	DFCN: CrackSegNet	Digital camera	409 images	Crack width	Tunnels
27	Qu et al. (2020)	VGG16 and LeNet-5	Digital camera	1500 images	Artificial scratch	Concrete pavement
28	Song et al. (Song 2020)	DCNN: CrackSegNet	High-speed mobile camera	8188 images	Crack width	Concrete pavement
29	Liu et al. (2020)	DCNN	UAV	3200 images	Hairlines	Concrete building
30	McLaughlin et al. (2020)	CNN	Lidar	120 images	Delamination and spalling	Concrete bridges
31	Su and Wang (2020)	FCN	Smartphone camera	12000 images	Crack width	Concrete bridges
32	Hsieh and Tsai (2020)	FCN and U-net	High-speed vehicle camera	1562 images	Crack width	Concrete pavement
33	Kumar et al. (2021)	YOLO v3	Web camera	800 images	Crack and spalling	Concrete bridges
34	Wei et al. (2021)	DCNN	Digital camera	-	Bug holes	Concrete cylinder specimen
35	Meng et al. (2021)	ResNet101	Digital camera	1695 images	Crack width	Concrete bridges
36	Liu and Yeoh (2021)	DISTS: Deep image structure and texture similarity	Digital camera	2000 images	Longitudinal, transversal, diagonal,	Concrete building

NO	Author	Image Processing	Data Source	Dataset	Defect Category	Object
					and hairlines crack	
37	Yu et al. (2022)	YOLO v5	Digital camera	1000 images	Crack and spalling	Concrete bridges
38	Wu et al. (2022)	FCN	High-speed mobile camera	90 images	Crack width	Concrete pavement
39	Ha et al. (2022)	SqueezeNet, U-Net, and MobileNet-SSD	Patrol vehicle road scanner camera	1330 images	Alligator, longitudinal, transverse, and patching crack	Concrete pavement

As shown in Table 2, computer vision in image processing for detecting concrete cracks in 2017 and earlier still uses traditional methods such as edge detection; in those years, they have not used deep learning-based image segmentation. It can be inferred that these methods have been used for decades. The technique used for image segmentation and image processing is still fighting a losing battle to construct the algorithm from the bottom up. Meanwhile 2017, a significant increase in the usage of deep learning-based image processing algorithms was seen. Many deep learning-based algorithms, including AlexNet, VGGNet, and ResNet, were developed after 2014 (Bulat & Tzimiropoulos, 2016). Compared to other sectors, technology for processing images using deep learning often occurs later in the field of civil engineering. However, the application of image processing to identify cracks in concrete is usually carried out in the order listed, such as crack detection in concrete pavement, concrete walls, bridges, buildings, and tunnels.

Many image processing algorithms have been used to detect cracks in concrete. The image processing algorithm for concrete crack detection can be seen in figure 4.

Figure 4 Percentage using of image processing algorithm in concrete defect detection.

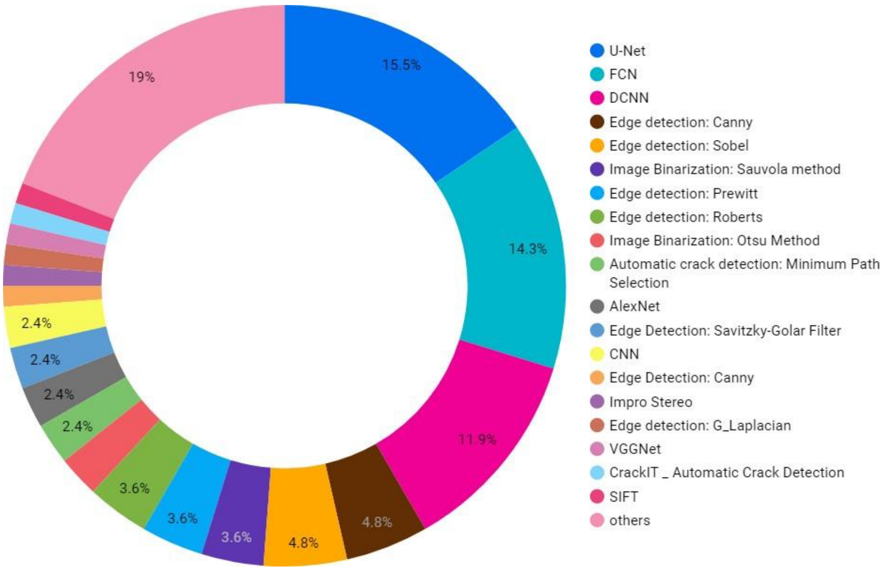

Figure 4 shows that the three most widely used algorithms are U-Net at 15.5%, FCN at 14.3%, and DCNN at 11.9%. The rest is the traditional sequential method algorithm is the edge detection of Canny and Sobel respectively 4.8%. Sauvola's image binarization method contributed 3.6%. It is impossible to detach the phenomenon of the predominance of the use of deep learning-based algorithms from the fact that the algorithm has been extensively developed and can be easily used directly without having to think about the computational development of the algorithm. It enables researchers to concentrate on the engineering problem of concrete cracks. An illustration of the percentage usage of image processing methods that have been used in the identification of concrete defects during the last 10 years can be seen in figure 5.

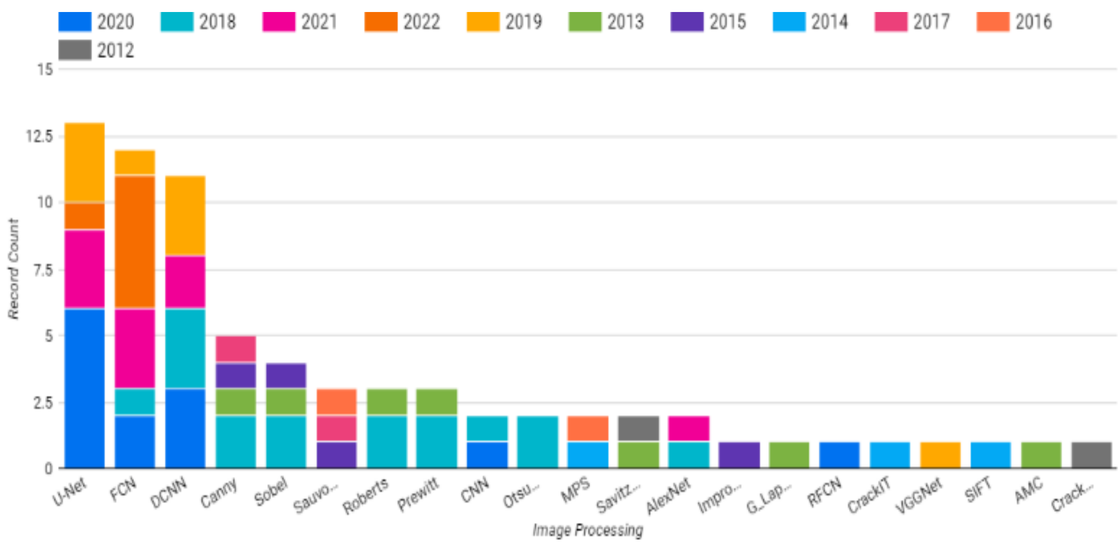

Figure 5 Percentage using of image processing algorithm in concrete defect detection.

Figure 5 demonstrates that the U-Net algorithm is the one that is used the most frequently, with a total of 13 applications, with the details of 2020 being used the most frequently, with a total of 6 applications, followed by 2019 and 2021, with three applications each, and 2022, with a single application. Then, FCN will appear five times in 2022, three times in 2021, three times in 2020, and once each in 2018 and 2019. Because these three methods can automatically extract important features from the detected concrete cracks image object, the computational process is also faster than other image processing algorithms. The U-Net, FCN, and DCNN algorithms have recently seen a marked increase in their use. Edge detection-based crack detection, such as Canny and Sobel, is also frequently used to detect cracks in concrete. In this method, edge detection shows the boundary between two detection areas with the same homogeneity level. Areas that are very far apart will be detected as edges. However, in this scenario, the area can be a crack that has already occurred.

Digital cameras, webcams, UAVs, and other sources that have continued to rise in popularity over the last ten years may be used to get datasets that can be used in the image segmentation process for concrete cracks. Its evolution can be observed in figure 6.

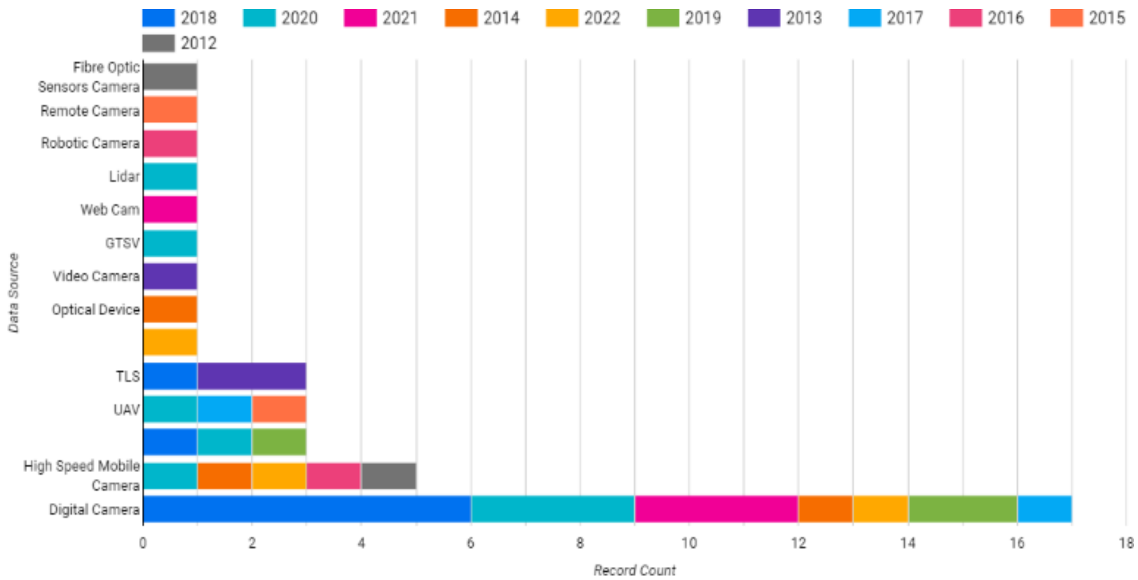

Figure 6 Trend data source image processing algorithm in concrete defect detection.

Figure 6 shows that over the last 10 years, there has been a growing tendency toward using datasets for image processing to identify concrete damage. This movement has been heavily driven by several variables, including the following:

Utilizing UAV technology on an item of study, such as the object of the bridge, will make it simple to inspect any damage to the bridge's concrete structure. Additionally, employing UAV technology will make inspecting towering structures safer and more expedient. Since 2013, unmanned aerial vehicles (UAVs) have become increasingly common on bridges. This is because the Structural Health and Monitoring System (SHM) technology was commonly used for the inspection of bridge structures up until 2013. However, beginning in 2013, SHM began transitioning to using a UAV system that was combined with computer vision-based deep learning.

The location of the object of research, from the beginning of 2010 to 2015, the collection of datasets for image segmentation remains largely utilizes automated high-speed cameras, digital sensors, and robot camera systems whose prices are still extremely costly, so this impacts the object of research on crack detection in the concrete structure so that in 2015 and below the object of research on concrete crack is still limited to the concrete pavement and concrete wall, where the image selection is easy.

The evolution of the image processing algorithm is closely tied to the advancement of cameras as a data retrieval media. To get datasets in 2015 and earlier years, it is still necessary to use a robot camera, which is very expensive, which is one reason why there is not a significant amount of data obtained. Since 2015, the usage of digital cameras, UAVs, and smartphone cameras has expanded to the point that the related datasets have also increased. In addition, the simplicity with which data may be processed has been supplemented by developing more sophisticated algorithms.

Conclusion

This study aims to offer a comprehensive assessment of the many image-processing approaches that have been applied to the problem of locating cracks in concrete. The primary objective of this research was to investigate and evaluate a crack detection system mostly based on image processing. For this analysis, we selected 40 research publications focused on crack identification. The evaluation we conducted based on examining the four aspects is now complete. The first method is the defect category, which considers factors such as surface crack, hairlines, crack width, crack pattern, void, diagonal crack, and longitudinal and transversal crack. Second, the position and location of cracks in objects constructed of concrete, such as concrete pavement, concrete bridges, concrete buildings, concrete walls, and concrete cylinder specimens, is the object of detection that has to be found. Third, the dataset source uses devices such as digital cameras, cameras built into smartphones, camera sensor systems, high-speed cameras, robot cameras, and UAVs. In the end, we completed the analysis based on the image processing methods used by each system.

In addition to this section, further research areas may prove useful in further investigating image processing-based concrete crack detection. According to the results of the survey, it is possible to draw the conclusion that the advancement of image processing algorithms and camera technology that is based on computer vision holds a great deal of promise for research in the field of image segmentation and image processing for concrete defect detection in the years to come. Image processing as a technique shows great promise for developing automated evaluation in concrete buildings, especially in high-risk areas for safety reasons.

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