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A Comprehensive Review of Image-Based Concrete Crack Analysis Using Deep Learning

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Abstract:
Due to the substantial urbanization brought about by the recent rapid increase in the human population, multistorey structures like skyscrapers that may house hundreds or even thousands of people have been built. In order to meet their operating objectives, industrial sectors also need tall, sturdy structures. In order to maintain structural integrity, ongoing auditing and maintenance are required due to the growing need for secure and dependable infrastructure and structures. At the moment, human expertise is largely relied upon for the examination and verification of these structures, with the auditor's judgment, prior experiences, and knowledge influencing the results. However, this procedure is prone to human error, which could have disastrous results if flaws—especially concrete cracks—are not found and fixed quickly.

This review paper looks at developments in the use of deep learning and image processing methods to identify concrete cracks. In addition to making, it possible to identify cracks, these technologies offer thorough evaluations of their dimensions, including length, width, and area, which are vital information for prompt repairs. Such methods guarantee increased precision and effectiveness in structural auditing by tackling the drawbacks of human-dependent procedures, which helps to improve safety and dependability in industrial and construction applications.

Keywords: Image Processing, Crack detection, analysis, DL.

1. Introduction

Cracks are a crucial cause that affect safety, durability and functionality of the layout. The crack on the surface can spread and grow deep causing stress in a particular area, which will lead to structure failure. As they usually occur in concrete surfaces and the cracking of these surfaces is inevitable. Hazardous and corrosive chemical can enter the structure through cracks in concrete, endangering its structure and aesthetic integrity The performance metrics PSNR, MSE, NC is used for the quality checks of the images on completion of the process. The quality of watermarked image to host image, extracted watermark to the original watermark, host image to the watermark extracted host can be checked and analysed.

Types and causes of Cracks

Cracks can be categorised according to their timing, depth, width, and direction. They are divided into three width categories: narrow (less than 1 mm), medium (1–2 mm), and wide (more than 2 mm).

Cracks can be categorised as horizontal, vertical, diagonal, or stair-step depending on their direction. In poured concrete foundations, vertical fissures are usually low risk and are frequently caused by shrinkage or heat stress. Settlement is frequently the cause of diagonal cracks [33].

Table1: Classification of cracks based on width

Based on width	
Type	Width
Thin	<1mm
Medium	1-2 mm
Wide	>2mm

Surface cracks are crucial indicators of structural deterioration and durability practically in different types of buildings. As a result, visual inspection of building parts is essential for finding cracks and assessing physical and functional issues. However, fracture detection in structures is often done manually, especially in developing countries. As a result, implementing, measuring and gathering all the required data will be time consuming. Furthermore, because it is based on inspectors' moral judgment, manual visual examination is inadequate in terms of time, cost and precision. As a result, it is critical to replace building inspectors delayed and subjective examination with an automated means of detection and evaluating surface cracks. According to recent studies, image processing techniques are increasingly being used to increase the efficiency of the structure crack detection These works demonstrate how visual inspection of vertical and horizontal structural components has been an essential part of civil engineering. The crack data may be utilized to diagnose the issue and choose the optimum rehabilitative plan for mending structures and avoiding catastrophic failures.

2. Methods

General crack detection model as shown in Figure1.

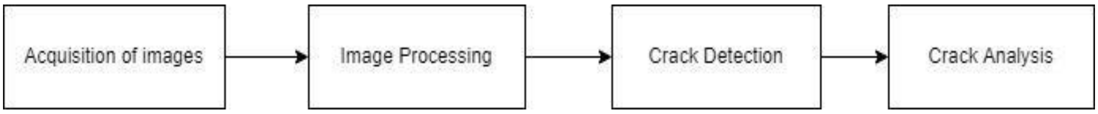

Figure 1: General structure for crack detection model

Very basic crack detection and analysis model includes, acquisition of image, image processing, crack detection and crack analysis. A digital image processing method is developed that detects and analyses fractures on architectural components automatically. The proposed model recognizes cracks pixels in image backdrops automatically, as well as crack parameters including area, perimeter, breath, length and direction. To improve the Otsu binarization approach, a pre-processing step known as Min-Max Gray Level Discrimination (M2GLD) is proposed in the proposed model, followed by shape analysis to improve crack detection performance. The proposed method's crack detection was compared to the traditional method's crack detection.

Computational methods

By providing effective and impartial non-destructive testing, automatic crack detection models overcome the drawbacks of traditional manual inspection. For crack detection, fully automated systems use machine learning, image processing, or a mix of the two. These computer-aided techniques, which improve accuracy and ease in evaluating structural degeneration, can be broadly categorised into image processing and machine learning approaches [34]

An image processing approaches

Concrete structure surface photos are analysed using image processing to determine the presence, position, and size of cracks. Important methods consist of:

By using a threshold, picture binarization transforms greyscale images into binary, allowing cracks (darker) to be distinguished from the backdrop (lighter).

Edge detection: pinpoints fractures for in-depth examination.

In order to improve identification, mathematical morphology [35][36] uses operations to refine crack properties.

Image acquisition is the first step in the process, which involves sampling and quantisation to transform analogue images to digital. Pre-processing is then done to improve image quality and lower noise for crack detection.

A machine vision-based model for automated crack identification with a single camera or a robot was created by Lins and Givigi [37]. After applying a crack detection algorithm to a set of photos, the model generates an output image that highlights the crack. The crack's pixel coordinates are saved in a vector, and a crack computation algorithm counts the pixels in a cross-section to calculate the crack's dimensions. The flow diagram of the proposed method is shown in Figure 2

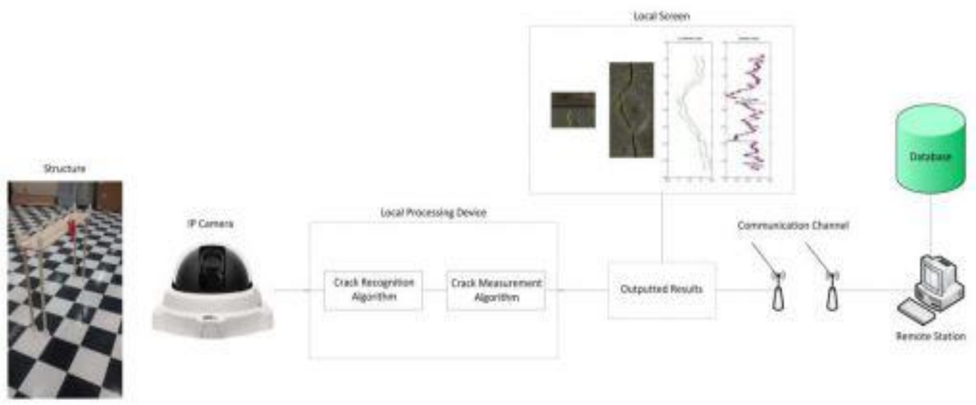

Figure.2: Flow diagram of the crack measurement system proposed [37]

Janani [38] suggested the following steps for an image processing-based crack detection method:

1)Image Loading: Open the matrix-formatted image of the concrete construction.

2)Noise Reduction and Greyscale Conversion: To minimise noise, employ median filters after converting the image to greyscale.

3)Enhancement and Restoration: Apply Wiener filters for blur/noise restoration and histogram equalisation to boost contrast.

4)Edge Detection: To find edges, use Sobel edge detectors.

5)Binary Conversion: To transform the image into a binary format (0 or 1), apply a threshold method.

6)Morphological Techniques: Use morphology to identify the edges of the structure and extract picture components.

Hamamoto and Yusuke [39] created a method for measuring crack lengths in noisy concrete surface photos in order to detect cracks.

Steps: Preprocessing to remove shading using median filtering. Detecting coarse cracks with a probabilistic method.

Detecting fine cracks with an adaptive threshold technique.

Using actual datasets of 60 noisy pictures, 90–95% accuracy was attained; however, robustness evaluation was limited

Shan [40] [41]: In order to determine crack width by figuring out the smallest gap between crack edges, it was suggested to project crack edge curves to 3D coordinates

Su [42] applied computer vision techniques to CCD images in order to detect cracks in concrete structures.

Hoang [43]: used an enhanced Otsu technique for surface fracture detection and thresholding.

Shin [44]: used energy transmission from surface waves to locate cracks

Machine learning approaches

The goal of machine learning, a branch of artificial intelligence, is to build systems that can learn from their experiences and forecast the future. Models are trained using either labelled or unlabelled datasets. The model makes predictions and evaluates their correctness when new information is provided. The machine learning algorithm is used if the accuracy is satisfactory

Supervised Learning

Having both the raw input data and the results is necessary for supervised learning. [45] To begin, separate the data into training and test datasets. Then, train the network using training data set, whereas the test dataset is utilized to forecast results or assess our model's correctness.

Unsupervised Learning

In the unsupervised learning dataset, the training data set is not labelled or classified. Unsupervised learning defines a hidden structure by inferring a feature from an unlabelled data set. Unsupervised learning's primary issue is identifying patterns in the data. The model can forecast the pattern of any data collection once it can generate patterns.

Reinforcement Learning

Because it lacks labelled datasets and data-related outcomes, a task is completed by experience-based learning. For every action that is done correctly, it receives positive reinforcement; for every action that is done incorrectly, it receives negative reinforcement. It gains knowledge about what should and shouldn't be done from this. Both the gaming industry and industrial automation make extensive use of reinforcement learning.

Using several classification techniques and extracted functions or feature descriptors, Jitendra [46] suggests a classification model. Yamaguchi [47] employs percolation-based image processing and the termination-and-skip-added approach to cut down on processing time.

Deep learning approaches

One machine learning technique that has recently been employed as a successful crack detection tool is deep learning. Algorithms developed using artificial intelligence are known as deep learning algorithms [48] [116].

Two methods for classifying images are contrasted in the article. Three steps are involved in Csurka et al.'s[49] Bag-of-Words model: feature extraction to determine the attributes of an image, visual vocabulary construction to generate visual words, and classification to classify objects.

The technique used by Kim et al. [50] focuses on categorizing crack images by locating Crack Candidate Regions (CCRs) using color and shape. After binarization, CCRs are taken out and processed using CNN-based and SURF-based methods to create classification models. Images are separated into fixed-resolution sub-images once CCRs are detected by Sauvola's binarization. In the classification phase, labels are assigned using CNN and global features. Sauvola's binarization method is adopted for detecting the CCRs in this model as shown in Figure 3.

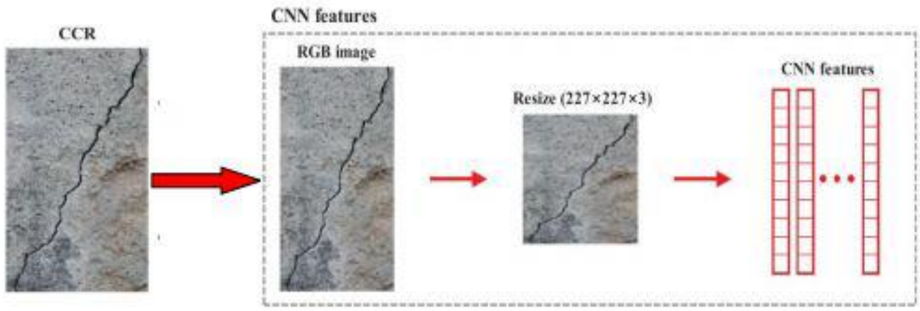

Figure.3: Feature extraction process of CNN[50]

Gang et al. [51] proposed an algorithm based on deep learning techniques for concrete surface crack detection. Images for the detection were taken from various completed construction sites using a mobile camera, and the main conclusions of their studies are as follows and shown in Figure 4.

1) Convolutional neural network structures are used for image recognition purpose as they overcome real environmental interference such as light and distance.

2) This CNN based model shows an accuracy of 93.7%.

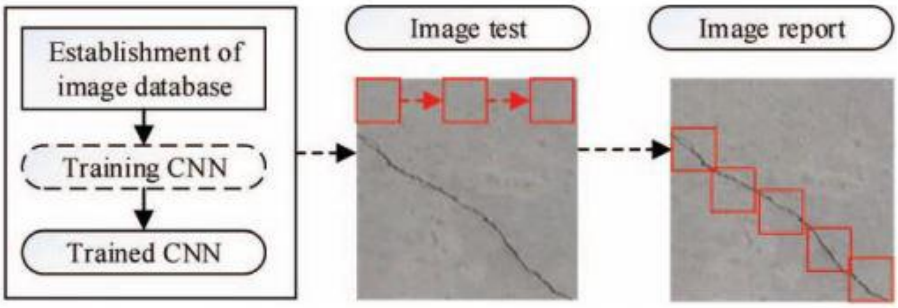

Figure.4: Crack detecting process framework [51]

Silva and Lucena [52] developed a crack detecting tool based on machine learning utilizing convolutional neural network [53] A heterogeneous dataset, i.e., photos with different light, surface polish and humidity that a concrete surface might exhibit were utilized to construct this model.

Li and Zhao [54] presented a convolutional neural network-based technique for picture crack identification. One of the greatest pre-built models for picture classification is AlexNet [55]. The suggested approach developed a binary classifier for crack detection by altering the AlexNet architecture

Feng [56], Islam [57], and Yao [51] applied convolutional neural networks (CNNs) and their variants for automated surface crack detection and identification. These methods effectively utilize deep neural networks for feature extraction and classification. To enhance usability, the trained CNN model is integrated into a smartphone application called Crack Detector, enabling accurate detection of cracks on real concrete surfaces without noise.

Deep learning's impact surpasses that of many earlier technologies, which is indicative of the quick advancement of computer science and technology [58,59].

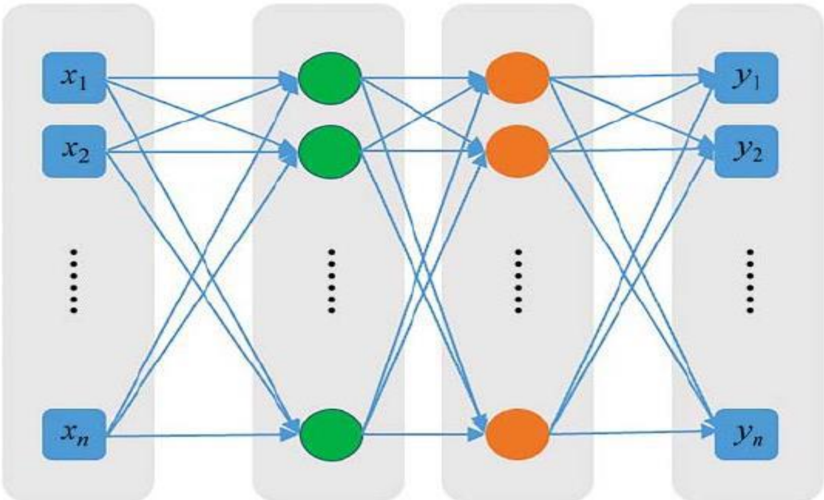

Figure:5. Convolution neural network model.

The input layer in image processing is where raw data, like RGB or grayscale images, are represented. The summary layer employs convolution operations, which entail cross-multiplication with input matrices, to extract features using specified convolution kernels (such as 3×3 or 5×5). Stochastic gradient descent is used to create the starting weights of the convolution kernel at random and modify them during training. Connection layers reduce the dimensionality of data by mapping extracted features in a thorough manner. Lastly, findings are provided by the output layer in formats that are customized to meet particular needs.

Deep Dictionary Learning and Encoding Networks

A good dictionary can rebuild the signal's reconstruction ability. Thus, sparse representation has been researched since the 1990s and is a crucial stage in dictionary learning. S. Mallat et al. [60] originally proposed dictionary learning in 1993.

A strong basis for dictionary learning was established by their overly comprehensive dictionary theory. A sparsity-based dictionary learning method was put forth by B.A. Olshausen et al. [61,62], which encouraged the growth of sparse representation and increased academic interest in dictionary learning.

Because certain dictionaries are created by hand under due to some mathematical limitations and their inability to adequately depict intricate natural image structures, researchers have recently turned to learning dictionaries directly created numerous dictionaries learning techniques using picture data [63–66]. Dictionary learning aims to provide a sparse representation of the original signal, and the sparse representation that is produced has a high capacity to represent the original data [67][115].

Dictionary learning can extract information with a certain utilization value by compressing the great majority of redundant information in the available input. The process of recreating raw data, or using training to obtain the associated dictionary matrix, is known as dictionary training. These dictionaries fall into two categories. The first category consists of fixed dictionaries, including the Wavelets dictionary [70], Curve Let dictionary [69], and Discrete Cosine Transform (DCT) dictionary [68]. The second kind is an adaptive dictionary, which is appropriate for unique signals and learns the characteristics of the given image to better achieve sparsity.

Image processing makes extensive use of dictionary learning. It has been used in many practical applications and is highly effective at solving issues like noise removal from images, image restoration through various transformations [71], pixel composition analysis of images [72], sound differentiation [73], and situation-specific image classification [74]. This paper's focus is on fracture detection in order to locate and examine the crack image. We use a technique known as DDLCN, which combines dictionary learning and deep learning and has strong representation ability [75]. DDLCN replaces the original convolution layer with a new learning encoding layer, combining the benefits of both. The fundamental idea of DDLCN is to use a dictionary learning encoding layer in place of the conventional convolution layer.

System architecture

This architecture model explains the general design of the crack detection model for detection of concrete cracks on various concrete surfaces. The design will help to detect and analyze fractures on several construction substances after it has been erected.

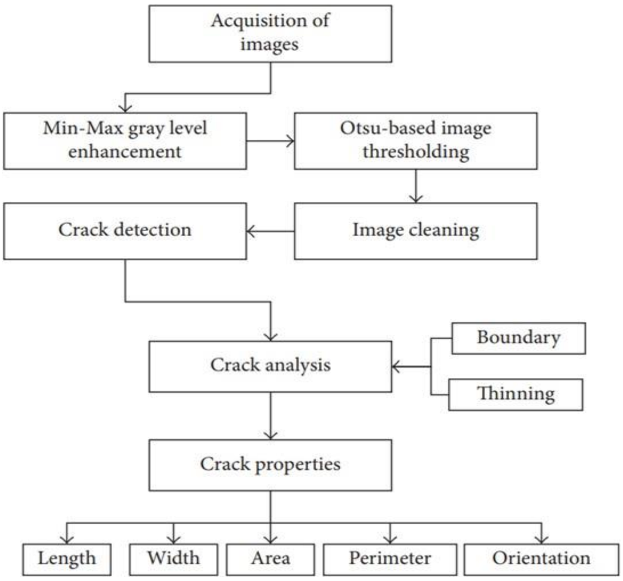

Figure 6: Crack Detection Model

The story of a system is represented graphically in an architecture diagram. Figure 6 depicts the general layout of a crack detection model the figure depicts phases such as acquisition of image, applying image processing techniques on datasets, analyzing the crack, and prediction if the crack is dangerous or not.

A variety of techniques for crack detection utilizing image processing methods have been established and categorized according to their methodologies [23].

A. Data preprocessing

The goal of this phase is to get the crack dataset ready for modeling. The following steps are included in the prepossessing stage:

1) Obtaining the Dataset: A dataset is a curated group of digital pictures used by computer vision developers to test, train, and assess the performance of their algorithms.
2) Importing libraries: Import libraries that have previously been declared in Python. These libraries are used for many different purposes. We will use three specific libraries for data preprocessing: Numpy, Pandas, and Matplotlib.
3) Importing datasets: Import the datasets for concrete crack analysis that we have gathered.
4) Feature scaling: A standardized method used for varying the quantities that is the magnitude of various values within a given limit or limits. It is used extensively during the data pre-processing stage in various AI/ML models
5) A combination of Otsu algorithm and M2GLD is used in tandem to perform image thresholding over the original image captured from a digital camera, this gives an improved method to perform image analysis.

B. OTSU METHODS

A notable picture background subtraction approach is the Otsu method. The basic concept behind this strategy is to split pixels in an image in two groups. The ratios of the pixel density to the standard grey value, which define a separated item, $\omega 0$ and $\mu 0$. The background of the picture, has two variables: $\omega 1$ and $\mu 1$. As a result, the overall greyish intensity of the image is formulated as having

$\mu = \omega 0(t)\ \mu 0(t) + \omega 1(t)\ \mu 1(t)$

i.e., 't' specifies the image's grey level.

The crack is ideally binarized if the following optimization function, fs(t), is maximised:

C. Thresholding

Thresholding is the basic method used in almost all types of systems for crack detection. In general, thresholding is the simplest technique to understand, where we divide the image into objects and background, which would ultimately result in edge detection. The thresholding value may either be given or calculated by an appropriate method based on the histogram of the image [24-32]

D. Edge Detection

Edge detection algorithms are sensitive to the selection and determination of their parameters. The efficient performance of an edge detector for crack detection requires the selection of appropriate parameters for effective crack inspections. Since a single method may not be suitable for all images, edge detection can have superior preprocessing to increase its performance.

3. Related Work

Concrete crack in construction it affects the building infrastructure and safety due to which its effects the structural design of the building. Cracks in the bullying happens due to various different reasons, aging of the building, chemical reaction and so on. Many academics have proposed different models that detect cracks based on the images. Detecting cracks from images is the faster and cost-effective. This will help the inspector to detect the crack in more efficient way and time consuming. In this research, Shuai Teng, Zong Chao Liu, Gongfa Chen, and Li Cheng [3] examined the detection performance of 11 well-known CNN models used as YOLO v2 feature extractors. The parametric studies listed below were carried out. According to a study of 11 well-known network models, the'resnet18' has a high precision (AP = 0.89) and speedy processing performance. Selecting the appropriate feature extraction layer can improve detection outcomes. Layers that are too shallow or too deep might also create unsatisfactory detection results. As the resolution of the photos used rises, the detection precision improves. Visuals have an impact on the breadth of the experiment and the detection outcomes. Finally, the working mechanism of the feature extractor was unveiled. Youm, Minkyo, et al. [18] proposed a machine-driven image-based approach system that detects the images based on the cracks.

The crack is analyzed by calculating the area length and width which will help to detect whether the crack is dangerous. Teng,shuai,et al.[3]proposed an idea where it detects the crack and digitally captures damage flaws. Talab, Ahmed Mahgoub Ahmed,et al.[17] projected computerized identification of crack based on images and also evaluate the post collapse of the building and proposed method that can provide significant improvements in post-disaster building element analysis based on a numerical experiment. Hyunwoo et al. [11] offer an edge-based crack identification method based on the crack width transform. There are five steps to this approach. The crack candidate pixels are discovered and categorized from the opposing edges in the first stage, and a width map is created. To reduce the noise, the second stage employs aspect ratio filtering. In the following two phases, missing pixels are found and restored, and residual noise is eliminated using picture adaptive thresholding. Ahong et al. [8] proposed a model based on genetic programming and percolation model to detect the surface crack. To detect the surface crack, the cracks are retrieved using GP and calculates the crack tip in the second step. The cracks are detected using high-speed percolation with excellent precision. The fracture unit locations are scanned simultaneously to establish the link. In the end, the retrieved cracks are attached to the percolation-detected

Cracks, and the stack involvement area is eliminated to reveal the genuine fissures in concrete surface. Zhong et al. [10] have developed a considerably improved approach for detecting concrete surface cracks. In this procedure, the pictures are processed using an improved pre-extraction and an additional percolation methodology. Kim,Hyunjun,et al.[15] implemented a method where the images are converted into grayscale and remove the noise

With the help of binarization the cracks are shown in black and white where background is in white and cracks are in black. The cracks are detected in vertical and horizontal axes. Kim,Coung Nguyen,et al.[2] the accuracy of the data in the model it depends on the given input .The used GA to determine how to improve the settings of IPTs when the IPT data was combined with the DCNN approach, resulting in a high level of automatic fracture identification. Image processing techniques are divided into three categories. The three sections are image filtering, binary image, and feature extraction. a GA sequence consisting of the three key stages. Gang Yao,Fu-JiaWei,Ji-Ye Qian,Zhao-Guo Wu [8]

The image recognition of concrete surface cracks using a convolution neural network is researched in order to detect cracks in concrete surfaces quickly and reliably. With the help of mobile phone camera, the images are collected from various construction site, based on deep learning the advanced aspects of concrete surface images. It is possible to extract images that efficiently avoid noise effects. With the classification result of 93.7 percent. The CNN research reported that it performed well in detection of crack. Moreover, additional research is needed to provide a uniform database. A convolutional neural network structure was built for picture recognition of concrete surface cracks.

The literature surrounding automated crack detection in building materials using image processing and deep learning has evolved significantly over the past few years, reflecting advancements in both technology and methodology. The foundational work by [22] established a comprehensive crack detection system leveraging unmanned aerial vehicles (UAVs) and digital image processing techniques. This study highlighted the effectiveness of integrating various image processing methods, including Otsu's method and fuzzy C-means clustering, for detecting cracks in concrete surfaces. By comparing spatial and frequency domain techniques, the authors underscored the potential of deep learning neural networks in enhancing the accuracy of automated inspections.

Deep learning's [82] explosive growth has caused significant disruption in the tech sector. It is extensively used in numerous applications, such as semantic segmentation [86, 87], object classification [83–85], data augmentation [88, 89], and hyperparameter forecasting [90]. The Back Propagation Network (BP Network) [91], Support Vector Machine (SVM)[92], and Convolutional Neural Network (CNN)[93] are only a few of the groundbreaking efforts in the field of deep learning.

Evaluation Metrics

TPR=(TP)/(TP+FN)

TNR=(TN)/(FP+TN)

F1=2TP/(2TP+FN+FP)

4 Results and discussion

Table 2: Results of comparison with other deep learning algorithms.

Dataset	Traditional Deep Learning Algorithms				Transformer Algorithm			
	Methods	P(%)	R(%)	F1-Score(%)	Methods	P(%)	R(%)	F1Score(%)
	Segnet	73.2	81.2	77.0	VIT	82.6	83.7	83.2
	Deep Crack	53.5	55.5	54.5	Swin-UNet	85.7	83.6	84.6
DeepCrack	RCF	60.1	71.3	65.2	Trans UNet	86.2	84.4	85.3
	Literature [76]	82.8	83.7	83.2	ours	88.9	85.7	87.2
	ours	88.9	85.7	87.2				
Crack Forest Dataset	Segnet	42.0	60.2	49.5	VIT	58.6	77.7	66.7
	DeepCrack	46.7	61.5	53.0	Swin-UNet	60.7	75.3	67.2
	RCF	41.5	49.5	45.2	Trans U Net	63.8	79.8	70.9
	Literature [77]	61.7	72.5	65.4	ours	63.2	81.2	71.1
	Ours	63.2	81.2	71.1				
RID	Segnet	37.2	51.6	43.2	VIT	48.6	51.7	50.1
	DeepCrack	39.3	51.4	44.5	Swin-UNet	52.8	50.9	51.8
	RCF	40.6	49.8	44.7	Trans U Net	53.2	54.6	7.9
	Literature [42]	61.7	72.5	65.4	ours	58.9	52.3	55.4
	Ours	58.9	52.3	55.4				

Table 2 displays the comparison results with various widely used techniques. Additionally, our approach outperforms SegNet [79], RCF [40], DeepCrack [78], and Lit-eratures [80], [81] in terms of accuracy. In addition to having F1-scores that are 10.2% higher than SegNet's, the DeepCrack Dataset also has recall and precision that are, respectively, 15.7% and 4.5% better.

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Image Processing Based Crack Detection

Table 3. Image Processing Methods for Crack Detection.

Method	Features	Domain	Image Details	Imaging Device/Source	Results	Limitations	Ref.
Recursive Tree edge pruning	Crack Detection	Pavement	206 images 800 _ 600	-	Precision = 0.79 Recall = 0.92 F-Measure = 0.85	Increased runtime (up to 30 s)	[94]
GP and Image Filtering	Crack Detection	Concrete	17 (Varying resolution)	Digital Camera	Accuracy = 80%	-	[95]
Gabor Filter	Crack Detection	Pavement	5 336 _ 339 pixels	Canon IXUS 80 IS	Precision up to 95%	Results presented on 5 images only	[96]
Particle Filter	Crack Detection & Measurement	Civil Structures	14 12 MP	IP Camera	Error Range = 7.51–8.59%	-	[97]
Beamlet Transform	Crack Detection & Measurement	Pavement	256 _ 256 pixels		A method is fast & robust to noise	Can't calculate crack width; manual setting of thresholds prevents full automation	[98]
Median filter, Hessian Matrix, probabilistic relaxation	Crack Detection	Noisy Concrete Surfaces	60 images 640 480 pixels	SONY Cyber-shot DSC-F828	AUC = 0.9903	-	[99]
FPHBN	Crack Detection	Pavement	500 + 1969 + 206 + 118 + 38 (Varying resolution)	Crack500, GAPs384, CrackTree200, CFD, Aigle-RN	AIU = 0.081 Time = 0.241 s/image	Method is not real time	[100]
Canny edge detector, dilate operators, Frangi filter	Crack Detection	Bridges	72 images 4288 *2848 resolution	UAV	Detection rate = 98.7%		[101]
UAS Operator	Crack Detection & Measurement	Bridges	Real-time crack detection	DJI Mavic Pro	DJI Mavic Pro most suitable camera to visualize cracks	UAS not stable in the absence of GPS and windy atmosphere	[102]
Shi-Tomasi feature point detection	Crack Detection	Bridges	Real-time crack detection	Consumer grade digital camera	The system is robust to varying illumination conditions and complex textures	Accuracy affected by noise-limited camera resolution	[103]

Tree Structures

The existence of noise in the photos, which makes it challenging to identify fracture pixels, is one of the several difficulties researchers have while crack identification [94][100][101] Minimum spanning trees (MSTs) were built which show all the possible links of the determined crack sources. The unwanted edges were eliminated to get the output crack curves. The dataset for validation of the model consisted of 206 pavement images. The system takes up to 16 s to determine cracks from an input image. The precision-recall and F-measure values have been recorded as 0.79, 0.92 and 0.85 respectively indicating high accuracy and significance of the methods.

Genetic Programming

Nishikawa et al. used image processing techniques to automatically identify cracks in pictures of concrete. Genetic programming (GP) is used to identify major cracks [104]

Image Filters

A Gabor filter is a type of linear filter that examines a region's texture to identify information with a specific frequency in a given direction. As a result, this technique is highly successful in identifying fractures in pavements with a variety of textures. The trial findings revealed a 95% accuracy rate.

Beamlet Transform.

A beamlet transform approach was put out by Ying and Salari to identify and categorise fractures in pavement photos. An arrangement of line segments at different angles, scales, and places is called a beamlet [105]. Edges and lines are examples of linear features that can be extracted from photos using this technique.

Unmanned Aerial System (UAS)-Based Approach.

Crack identification from bridge photos was the focus of Dorafshan et al.'s work. The effects of lighting and crack distance from the camera on fracture identification outcomes were examined using a UAS. As a result, a metric known as "achievable crack to platform (ACP) distance" was assessed [106]. This measurement indicates the furthest the camera may be placed from the platform before a crack can be reliably identified. Out of all the cameras the system tested, the DJI Mavic Pro was the best camera utilised in the UAS for improving crack visibility. The UAS operator measured the length and width of each crack and adjusted lighting and distance until the crack was visible [107-110].

Shi-Tomasi Algorithm.

Kong and Li focused on identifying steel bridge flaws. The target bridge structure is used to record a brief movie. At every video frame, distinct features brought about by crack opening and closing are recorded [111]. To detect features, the Shi-Tomasi algorithm was used. To find cracks, the video stream's surface movement gaps in the bridge section were located and monitored. Results from experiments demonstrated this method's resilience and effectiveness even under different lighting conditions. One drawback is the greater reliance on camera resolution, since low-resolution movies showed lower accuracy [112–114].

5.Conclusion

The performance of existing algorithms for the detection of surface cracks is still not up to the mark when applied to images obtained from diverse sources. The quality of the image, complications of lighting, consistency of surface crack shapes due to occlusions and environmental effects, improper acquisition, absence of high-resolution images from all viewpoints, clusters of mini-cracks, and low contrast between the surface and its cracks are the other main impediments that need due consideration. The results of the work done on visual cryptography and Moreover, detection and identification of the cracks in the covered regions by dust and impurities are still the missing portion of the current research. Future research can be conducted using advanced image processing techniques and the integration of machine learning and artificial intelligence. An interdisciplinary approach related to computer science, software engineering, statistical image processing, sensors, robotics, and civil engineering is the potential way forward to create better methodologies

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