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Deep learning for detecting distresses in buildings and pavements: A critical gap analysis

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Abstract

Purpose: The massive number of pavements and buildings coupled with the limited inspection resources, both monetary and human, to detect distresses and recommend maintenance actions lead to rapid deterioration, decreased service life, lower level of service and increased community disruption. Therefore, this paper aims at providing (1) a state-of-the-art review of the literature with respect to deep learning techniques for detecting distress in both pavements and buildings; (2) research advancements per asset/structure type; and (3) future recommendations in deep learning applications for distress detection.

Design/methodology/approach: A critical analysis was conducted on 181 papers of deep learning-based cracks detection. A structured analysis was adopted so that major articles were analyzed according to their focus of study, employed methods, findings and limitations.

Findings: The utilization of deep learning to detect pavement cracks is advanced compared to assess and evaluate the structural health of buildings. There is a need for studies that compare different convolutional neural network (CNN) models to foster the development of an integrated solution that considers the data collection method. Further research is required to examine the setup, implementation, and running costs, frequency of capturing data, and deep learning tool. In conclusion, the future of applying deep learning algorithms in lieu of manual inspection for detecting distresses has shown promising results.

Practical implications: The availability of previous research and the required improvements in the proposed computational tools and models (e.g., artificial intelligence, deep learning, etc.) are triggering researchers and practitioners to enhance the distresses' inspection process and make better use of their limited resources.

Originality/Value: A critical and structured analysis of deep learning-based crack detection for pavement and buildings is conducted for the first time to enable novice researchers to highlight the knowledge gap in each article, as well as, building a knowledge base from the findings of other research to support developing future workable solutions.

Keywords

Deep Learning, CNN, Pavement cracks, distresses detection, structural health evaluation, highway maintenance.

1. Introduction

The utilization of emerging digital technologies in construction industry is vital to enhance the productivity, as well as, optimizing the utilization of resources (Goulding & Rahimian, 2012; Pour Rahimian et al., 2008; Elghaish and Abrishami, 2020). One of these technologies is the deep learning.

Traditionally, crack detection is based on manual inspection and dependence on professional's subjectivity. This initiated the need for reliable and efficient crack detection methods to improve the quality of the visual inspection results. Several automated or semiautomated computer-aided crack detection methods have been developed, such as histogram transforms (Patricio et al., 2005), threshold segmentation (Zhu et al., 2007), edge detection (Attoh-Okine & Ayenu-Prah, 2008; Zhao et al., 2010), region growing (Li et al., 2011; Zhou et al., 2016) etc.

Deep learning, as an extension of and subset to machine learning, has become a new research front in the field of crack detection due to its superior performance in object detection and semantic segmentation (J. Liu et al., 2020a; Abdelkader, 2021). With the evolution of computer-based techniques, the application of deep learning in detecting issues such as cracking where many studies were conducted to demonstrate crack detection using deep learning. To enhance the performance of crack detection, Zhang et al. (2019a) used residual network to develop a dilated convolution and multi-branch fusion strategies with different dilation rates. Another application of the deep convolutional neural network (CNN) and laser-scanned range images was developed by Zhou & Song (2020) to realize the pixel-level classification of cracks. Chen & Jahanshahi (2018) used CNN and Naïve Bayes to analyze individual video frames for crack detection.

Recently, deep learning has greatly endorsed computer vision development, which offers a feasible method for automated crack detection (Ogunseiju et al., 2021). Deep learning allows computers to learn from experience by using artificial neural networks and other machine learning algorithms (Xiong & Tang, 2021). This technique is 'deep' as it contains many layers that are used for feature extraction, transformation, and pattern analysis using supervised or unsupervised learning (Ongsulee, 2018). The key benefit of deep learning is that it supports a computational model composed of multiple processing layers to learn data representations with multiple levels of abstraction and trains the model on how to update internal parameters through backpropagation, without manual involvement in the design of feature engineering (Goodfellow et al., 2016). Generally, deep learning models contain three types of layers: input later, hidden layer, and output layer. The output of one layer is used as an input into the next one.

There are several architectures that can be implemented when it comes to deep learning (Saadi & Belhadef, 2019; Mansuri & Patel, 2021). Each of these architectures has its uses and compatibilities with certain applications. However, it should be noted that convolutional networks (CNNs/ConvNets) are the most common architecture for automated feature learning and supervised classification. CNNs with their capabilities related to the partial connections, sharing weights and pooling layers, can automatically capture the grid-like topology of images under fewer computations, and then generate promising detection results (Cha et al., 2017). CNN is used in image recognition by inserting the values from the image pixels to identify features (Jiang & Bai, 2020).

The key strength of CNN is in feature extraction and representation learning and the main weakness is its need for parameter tuning (Da'u & Salim, 2020). There are variations to the CNN technique such as region-based CNN (or R-CNN), fast R-CNN, and faster R-CNN. Support vector machine (SVM) was used to classify concrete images to crack and non-crack by using the handcrafted manual feature extraction (Na & Tao, 2012). Abdel-Qader et al. (2006) combined SVM with principal component analysis (PCA) to extract the healthy features out of a large set of features. Significant improvement to increase the accuracy of crack identification has been recognized after combining hybrid approaches with SVM such as fuzzy logic, genetic algorithm, artificial neural network (ANN), and k-nearest neighbors (k-NN) (Choudhary & Dey, 2012; Sri Preethaa & Sabari, 2020). However, the complexity of crack images makes the generalization performance of these traditional algorithms unproductive in efficiently managing a huge volume of cracks image features (Li et al., 2017).

There is a huge demand in the housing market and this requires to adopt unprecedent steps to build the required houses (Kolo et al., 2014). Therefore, Artificial Intelligence including deep learning can help in enhancing the productivity and avoiding rework.

Throughout the last two years, two review papers were published to analyze published deep learning publications in the built environment sector, for example, Akinosho et al. (2020) provided a comprehensive review of the general applications of deep learning in the construction industry, however, deep learning-based detection feature was not critically analysed and many articles have been published since the publication of this article. Given, the fact that the majority of deep learning applications in construction industry are associated with detecting objects including distresses of pavements and concrete and, as far as the authors are aware, there has not been a dedicated study that discusses and analyzes those application to enable researchers to enhance the existing solutions.

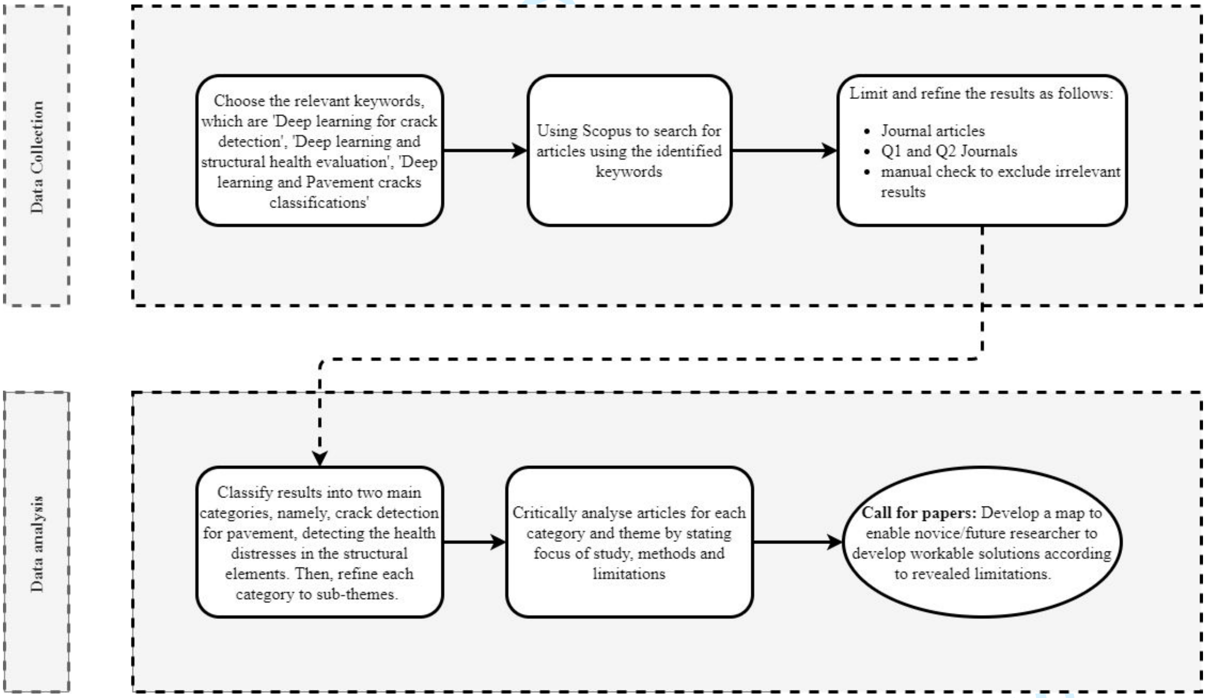
In lights of all those issues, this paper provides a deep analysis of major published articles of employing deep learning to detect and classify cracks for pavements and buildings. Given, most of published articles focused on utilizing deep learning to detect and classify a wide range of distresses in pavement and buildings, therefore, the objective of this research is to critically analyze published articles by highlighting the focus of each study, employed methods and limitations. As such, novice researchers can start developing workable solutions based on the recommendations of this research.

In accordance with the introductory information provided above, section 2, the methodology and logic of research is presented, followed by deep learning-based crack detection: a conceptual background is presented in section 3. Convolutional Neural Networks (CNN) for crack detection is described in section 4. Sections 5, 6, 7 and 8 present the critical analysis of deep learning-based crack detection for pavement and buildings, namely, relevant studies for deep learning-based pavement crack detection, deep learning-based concrete cracks detection, deep learning-based health structure evaluation, deep learning and Ground Penetrating Radar (GPR) to detect cracks. Thenceforth, discussion and significance are presented in section 9. Finally, the conclusion is presented in section 10.

2. Methodology and logic

stated that the mixed methods systematic review is the most effective method when the objective of the research is to define gaps in the body of knowledge and identify future research trends. Employing mixed methods systematic review enables researchers to form an objective presentation of the field. Mixed methods systematic review studies are superior to mono-method manual review studies in which researchers might be biased and their judgment and interpretation are subjective (He et al., 2017). Besides, relying on mixed methods systematic review enhances the depth and breadth of literature review studies (Heyvaert, 2017).

Figure 1 shows the research design and flow of the data collection and analysis. This paper focuses on the utilisation of deep learning to detect cracks/distresses for pavements and building structures. Therefore, the keywords that are used are specific such as (deep AND learning AND for AND crack AND detection) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SUBJAREA , "ENGI")) AND (LIMIT-TO (EXACTKEYWORD , "Crack Detection") OR LIMIT-TO (EXACTKEYWORD , "Convolutional Neural Networks") OR LIMIT-TO (EXACTKEYWORD , "Damage Detection") OR LIMIT-TO (EXACTKEYWORD , "Neural Networks")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (EXACTSRCTITLE , "Automation In Construction") OR LIMIT-TO (EXACTSRCTITLE , "Computer Aided Civil And Infrastructure Engineering").. The results were refined to include Q1 and Q2 Scopus journals to ensure the quality of sources. Given, Scan and skim techniques are recommended to find main themes of articles, as well as, finding relevant articles Machi & McEvoy (2008), therefore, the results were analysed and classified into two main themes such as 'Deep learning for pavement distresses' and 'Deep learning to



detect distresses in buildings structure'. Hereafter, sub-themes are developed from these two main themes. Most of articles were analysed in specific way, namely, focus of study, employed methods, findings, and the mentioned limitations in each article by authors. To avoid the cognitive bias, the mentioned systematic approach to find and list relevant studies, as well as consistent way of analysing articles were adopted. Moreover, using mentioned limitation(s) by articles' authors without judgements.

Figure 1. Research methods and logic

2.1. Deep learning-based crack detection publications per year

Figure 2 shows the number of publications per year. As shown in Figure 2, 181 papers have been published since 2017 and this reflects the high attention the application of deep learning to detect cracks for pavements and buildings has recently received over the past 4 years.

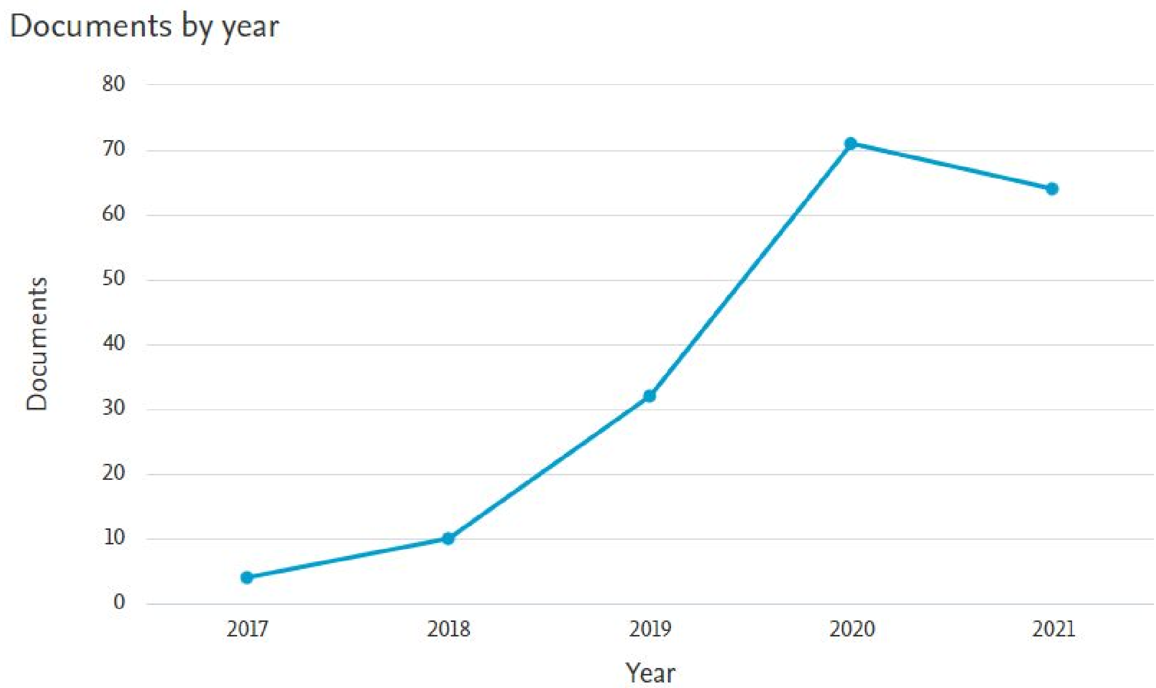


Figure 2. Deep learning-based crack detection publications per year

2.2. Progress of deep learning- based crack detection research per countries

Figure 3 depicts the allocation of 181 papers per countries. Around 45% of papers come from China, followed by United States that produced around 23% of total papers. Other 32% of papers were written in Canada, Australia, Singapore, UK, France, Honk Kong and India. The analysis of geographical allocation of publications works as an indication for future researcher to know the progress of research in this area over the world.

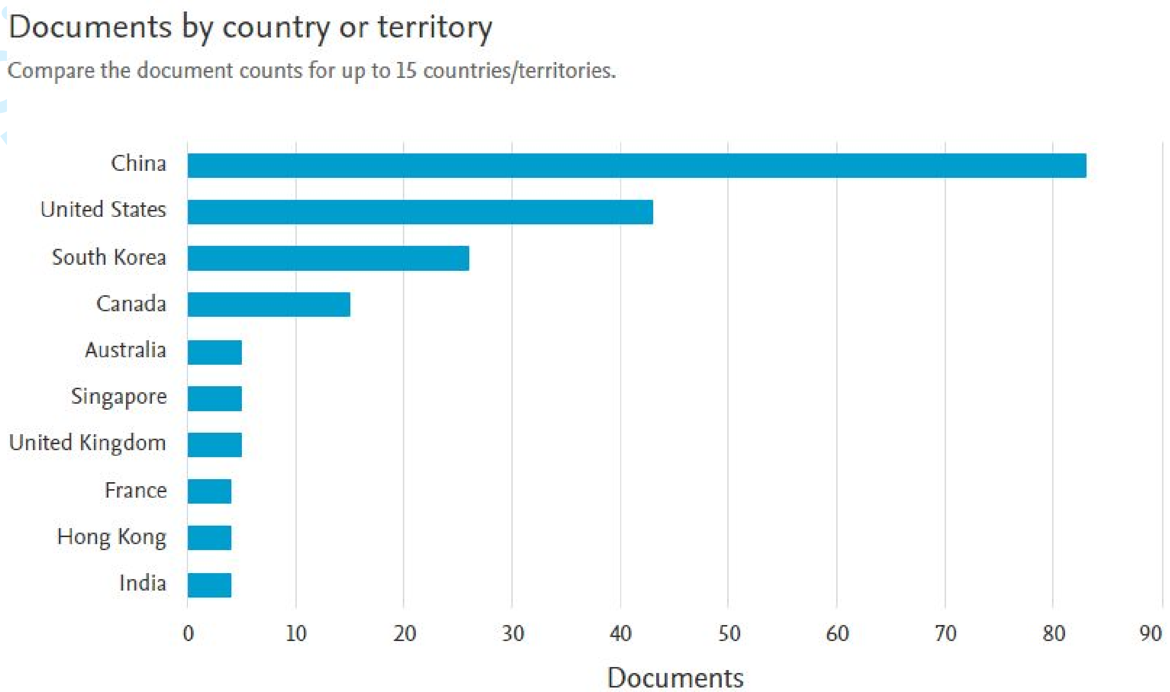


Figure 3. The geographical allocation of publications

3. Crack detection-based deep learning: A conceptual background

Deep learning region-based detection methods depend on window-sliding or region-proposal; in which continuous attempts of finding a bounding box for each possible object in an image is the essence of the process. R-CNN (region-based convolutional neural networks) uses selective search to produce regions, and then classifies these regions using a CNN. Cha et al. (2018) combined CNN with the sliding window technique to classify the crack and non-crack images more accurately. Zhang et al. (2018) used an R-CNN model to remove the noise areas before performing crack and sealed crack detection. However, this method (R-CNN) is impractical due to the huge effort required using the window-sliding-based when processing large number of images. In addition, the traditional region-proposal methods are inefficient in selecting good candidate regions from the noisy images (Uijlings et al., 2013). To improve the computation efficacy of region-based methods, H. Zhang et al. (2017) applied parallel processing, however, the computation and resource costs were expensive.

Fast R-CNN and Faster R-CNN improved the speed and accuracy of prediction by using the

Regional Proposal Network (RPN) to automatically produce the proposal (Ren et al., 2015). To detect cracks of images captured on concrete road surfaces, Hacıefendioğlu & Başağa (2021) developed a method using a pre-trained Faster R-CNN. Kang et al. (2020) developed an integrated method to automate crack location, segmentation and quantification using the integration of a faster region proposal convolutional neural network (Faster R-CNN) algorithm, modified TuFF method, and modified DTM for the crack detection and localization. Gou et al. (2019) used the Faster-R-CNN model for pavement crack detection. Cha et al. (2018) developed a Faster R-CNN to detect multiple types of damage including concrete cracks. Wang et al. (2018) also used Faster R-CNN for concrete damage detection in masonry historic structures.

Many efforts have been made to implement CNN-related methods in crack detection task, such as U-net convolutional neural networks that was proposed by Zhu et al. (2019) by developing a crack detection algorithm for U-net convolutional neural network, using U-net networks as the front end to extract the crack, and then using threshold method and Dijkstra connection to extract the crack accurately. However, this method was still difficult to solve the problem that features resolution degradation caused by continuous pooling. To increase the details of image features and enhance the effect of dense prediction, an Atrous Spatial Pyramid Pooling (ASPP) module was added to the U-net network by Chen et al. (2017) and Qiao et al. (2021).

Another lightweight end-to-end pixel-wise classification architecture called SegNet is employed by several researchers. For instance, Song et al. (2019) used it to train and test the SegNet model with 2068 bridge cracks images. Chen et al. (2020) applied it for inspecting concrete pavement, asphalt pavement, and bridge deck crack. Jun Zhao et al. (2020) employed it to solve the problems of illumination non-uniformity and impurities in asphalt pavement image. Finally, Ren et al. (2020) utilized it for efficient multiscale feature extraction, aggregation, and resolution reconstruction that greatly enhances the overall crack segmentation ability of the network.

CrackNet based on the convolution neural network was presented by A. Zhang et al. (2017) for automatic detection of pavement. CrackNet consists of five layers. The two input data layers are feature maps generated by the feature extractor. The output layer is the set of predicted class scores for all pixels. The two hidden layers are convolutional layers and fully connected layers. CrackNet includes more than one million parameters that are trained in the learning process to improve the accuracy of crack extraction. Inspired by CrackNet, Fei et al. (2020) proposed an automated pixel-level crack detection on 3D asphalt pavement images with deeper architecture and fewer parameters named CrackNet-V. Huyan et al. (2020) developed CrackU-net, which utilises convolution, pooling, transpose convolution, and concatenation operations, forming the "U"-shaped model architecture. Both, CrackNet-V and CrackU-net outperformed CrackNet in term of the calculation accuracy and efficiency.

In this article, a framework for feature selection and classification of cracks images is proposed based on three cascaded phases. The first phase automatically extracts features from the crack images by a CNN model. Then, a proposed feature selection algorithm, using Stochastic Fractal Search (SFS) and Guided Whale Optimization Algorithm (Guided WOA) techniques, is applied to properly select the valuable features. The last phase classifies the selected features by a proposed voting classifier, using Particle Swarm Optimization (PSO) and Guided WOA techniques to improve the ensemble's accuracy.

Huang et al. (2018) developed a two-stream semantic segmentation algorithm to detect crack and leakage in for metro shield tunnel based on deep learning. Feng et al. (2020) proposed a classification-based algorithm to detect cracks of different structures concrete surfaces for crack detection of a concrete dam surface (Cha et al., 2017). A similar method was implemented by Kim & Cho (2018) who collected images of cracks from the internet web search using ScrapeBox and then developed a classification algorithm based on deep neural networks. Other researchers developed a method for crack region segmentation using a mask region-based convolutional neural network (He et al., 2017; Kim & Cho, 2019).

An integration of a fully convolutional network (FCN) with a Gaussian-conditional random field (G-CRF), an uncertainty framework, and probability-based rejection was proposed by Tong et al. (2020) for detecting pavement defects. Lee et al. (2019) proposed a crack image generation algorithm using a 2D Gaussian kernel and the Brownian motion process to overcome the lack of data problem in crack detection. Jenkins et al. (2018) proposed a deep fully convolutional neural network to perform pixel-wise classification of surface cracks on road and pavement images. A more accurate and efficient crack detection process based on a spatial-channel hierarchical network (SCHNet) with a base net Visual Geometry Group 19 (VGG19), was proposed by Pan et al. (2020) for crack detection. Using the VGG19, Yang et al. (2018) developed a deep learning technique named fully convolutional network (FCN) to improve the efficiency of crack detection task. C. Zhang et al. (2020) developed an automatic pixel-level crack detection network based on instance segmentation to improve the Mask R-CNN network, which can output the type, location, and mask of the crack at the same time. A two-step pavement crack detection and segmentation method based on convolutional neural network was proposed by J. Liu et al. (2020b). Ayele et al. (2020) proposed an integrated set of UAV-assisted inspection and automatic damage identification process that comprises three key stages, (i) data collection and model training, (ii) 3D photogrammetry/construction, (iii) crack identification and segmentation, where deep learning-based data analytics and modelling are applied for processing and analysing drone image data and to perform damage assessment. A vision-based crack detection system based on a context-aware deep semantic segmentation network that integrates the pixel-wise prediction results from multiple local overlapping image patches was proposed by Zhang et al. (2019b). A modified architecture of FCNN was proposed and employed by Xu et al. (2019) for crack identification in the steel box girder of bridges containing complicated disturbing background and handwriting. An adversarial learning architecture of Semi-supervised was proposed by Li et al. (2020) and applied for pavement crack detection and by Shim et al. (2020) for Crack Detection in Concrete Structures.

4. Convolutional Neural Networks (CNN) for crack detection

Amongst many of the reviewed conventional deep learning architectures, Convolutional Neural Network (CNN) is widely known for their capability of capturing critical local-spatial features, hence producing promising results in crack detection (Cha et al., 2018).

Kumar & Ghosh (2020) developed a vision- based method using a deep architecture of convolutional neural networks (CNNs) for detecting concrete cracks without calculating the defect features. The designed CNN is trained on 40K images of 256 × 256-pixel resolutions to detect cracks by classifying each region separately. Chuang et al. (2019) pre-processed the image by Naive Bayes classifier and then identified cracks with the CNN. Hoang et al. (2018) compared a CNN model with metaheuristic optimized edge detection algorithm. The results of this study showed that the performance of CNN was significantly better than edge detector. A later study by Ye et al. (2019) put forward a structural crack detection method based on CNN, which divides the image and processes it with deep NN and random forest. However, the region-based methods can only provide information on the existence of cracks and rough shape and location depending on the size of regions. The value of crack detection decreases if the accurate pattern and location of the cracks cannot be given. Liang (2019) introduced a CNN approach for detecting concrete columns surface cracks or spalls. To overcome this issue, pixel-level crack detection methods are studied. For instance, the investigation conducted by Fan et al. (2019) improved the detection accuracy to 92.08% through the integration between the edge optimization algorithm and the CNN. Ni et al. (2019) proposed a convolutional neural network-based framework to automatically extract cracks and accurately at a pixel level, through convolutional feature fusion and pixel-level classification. Liu & Zhang (2020) presented a novel context-aware deep convolutional semantic segmentation network to effectively detect cracks in structural infrastructure under various conditions. The proposed method applies a pixel-wise deep semantic segmentation network to segment the cracks on images with arbitrary sizes without retraining the prediction network. Meanwhile, a context-aware fusion algorithm that leverages local cross-state and cross-space constraints was proposed by Won et al. (2020) to fuse the predictions of image patches through the adoption of U-Net to detect the concrete cracks. Focal loss function is selected as the evaluation function, and the Adam algorithm is applied for optimization. The trained U-Net is able to identify the crack locations from the input raw images under various conditions such as illumination, messy background, width of cracks, etc. with high effectiveness and robustness. Fan et al. (2020) developed a robust method for crack detection using the concept of transfer learning as an alternative to training an original neural network. Three standard deep learning methods of training a crack classifier are as follows: 1) a shallow convolutional neural network built from scratch, 2) the output features of the VGG16 network architecture previously trained on the general ImageNet dataset, and 3) the fine-tuned top layer of VGG16 is investigated. Data augmentation is used to reduce overfitting caused by the limited and imbalanced training dataset. The image dataset includes both fatigue test photographs and actual inspection photographs captured under uncontrolled distance, lighting, angle, and blurriness conditions. Zhu & Song (2020) developed a weakly supervised network for the segmentation and detection of cracks in asphalt concrete deck. Firstly, the data were differentiated by the autoencoder, and the unlabeled data features were highlighted, so that the original data autonomously generate a weakly supervised start point for convergence. Secondly, the features were classified by k-means clustering (KMC). Thirdly, the cracks in the bridge deck defects images was subjected to semantic segmentation under weak supervision. A dataset of six types of defects on asphalt concrete bridge deck, which was set up the defects in the dataset, was labelled manually. Recent research utilized cycle consistent generative adversarial learning for crack detection (Nath et al., 2020). In this study, the authors proposed a self-supervised structure learning network that can be trained without using neither paired data nor ground truths (GTs). This is achieved by training an additional reverse network to translate the output back to the input simultaneously.

In recent years, there has been an increasing interest in Whale Optimization Algorithm (WOA) that was proposed by Mirjalili & Lewis (2016). The concept of the WOA is inspired by the foraging behavior of whales. Bubbles are utilised to catch the prey by pushing them to the surface in a spiral shaped (Mirjalili & Lewis, 2016; Mirjalili et al., 2020). Recently, literature showed that WOA has a significant capacity in resolving complicated engineering optimization problems (Ling et al., 2017). Abdel-Basset et al. (2018) proposed a combination of WOA and a local search strategy to tackle the permutation flow shop scheduling problem. Mafarja & Mirjalili (2017) combined WOA with simulated annealing for feature extraction. Aljarah et al. (2018) proposed WOA-based trainer to train multilayer perceptron (MLP) neural networks. Moreover, there are also research bodies trying to utilise WOA to solve other problems, such as multi-objective optimization (Wang et al., 2017; Aziz et al., 2018; Got et al., 2020), image processing (Hassanien et al., 2017; Mostafa et al., 2017; Aziz et al., 2018), software testing (Harikarthik et al., 2019), and power system applications (Hasanien, 2018; Raj & Bhattacharyya, 2018). To implement this algorithm, three mechanisms should be modeled: (1) shrinking encircling prey, (2) bubble-net attacking method (exploitation phase) and (3) search for prey (exploration phase). The first mechanism is the prey encircling when the WOA initiates the best search agent by considering the current locations as the best location of the prey. The remaining agents accordingly adjust their locations to the best search agent. This can be expressed mathematically as stated by (Mirjalili & Lewis, 2016).

5. Relevant studies for deep learning-based pavement crack detection

Table 1 shows the major published research from 2017 to 2021 that focus on using deep learning to detect and classify cracks for pavement. Each paper was analyzed according to research aim (focus of study), methods, findings, and limitations to enable researchers to develop new solutions to address those limitations.

Table 1. Relevant research for deep learning-based pavement crack detection

Authors	Aim	Methodology	Findings	Limitation(s)
(Ali et al., 2021)	Provide a reference for researchers working in the field of crack detection and localization in concrete structures.	Applying five deep learning models, including a proposed customized CNN model,	Training a customized CNN model with a small amount of data and high performance is the best option for practical crack detection in concrete surfaces.	Customized CNN model is not able to analyze various characteristic of cracks, such as crack width, length, and orientation.
(Chun et al., 2021)	Overcome Weaknesses in Images and GIS Visualization for the detection of cracks in Asphalt pavement.	Using a convolutional neural network (CNN).	The model developed in this study showed high detection accuracy for pavement images with cracks.	Few false positives in pavement images without cracks caused by slender shadows and joints.
(Le et al., 2021))	Classify the cracked images efficiently, saving time, and avoiding high computational costs.	Image-based CNN recognition model for the detection of cracks on concrete surfaces.	The proposed CNN model improves the classification of cracked images.	Different types of cracks were not considered in this works.
(Yang et al., 2021)	Compare the superiority of the training model according to the test set; and then select the most suitable model based on the experimental results	Three neural networks, AlexNet, VGGNet13, and ResNet18, to recognize and classify crack images.	The tests indicate that the ResNet18 model generates the most satisfactory results.	Comparison is limited to three neural networks.
(Rao et al., 2021)	Detect crack/non-crack conditions of concrete structures from images.	Automated detection method based on CNN models and non-overlapping window-based approach.	The proposed approach outperforms existing models in terms of accuracy and inference time.	N/A
(Zhou &	Yield better	DCNN-based	The experimental cases	Difficulty in

Song, 2021)	classification performance with data fusion.	roadway crack classification methods.	demonstrate that the proposed data fusion approach can reduce false detections and thus improvement in the classification performance.	detecting cracks on surface regions that suffer from both low intensity contrast in the intensity image and shallow depth in the range image.
(Fang et al., 2020)	Develop a novel framework to address challenging vision problems.	Combination of Faster R-CNN for crack patch detection, a DCNN for crack orientation recognition, and a Bayesian algorithm for integration.	The proposed approach outperforms the state-of-the-art baseline approach on deep CNN classifier.	Risk of missing small cracks.
(Fan et al., 2020)	Develop an efficient automatic pavement crack detection and measurement model	Using an ensemble of CNN models.	The algorithm adequately performs crack measurement: the length and the width of different crack types can be measured with satisfactory accuracy.	Unable to perform end-to-end crack detection and can only be employed to detect static images.
(Feng et al., 2020)	Improve crack detection accuracy and generate a better detection box to surround the cracks.	Crack identification method based on a deep CNN fusion model.	The developed method can provide the category information for pavement cracks as well as the accurate positioning and geometric parameter information, which can be used directly for evaluating the pavement condition.	N/A
(Qu et al., 2020)	Improve the efficiency of crack detection.	Using convolutional neural network.	Percolation algorithms based on image processing have better detection results for the background of cleaner linear crack.	The effect of image with more complex cracks is poor especially with the background of interference Noise.
(Li & Zhao, 2019)	Detect cracks from images of concrete surface contains various types of noise, thin cracks, rough surface, shadows.	Image-based crack detection method using a deep convolutional neural network (CNN).	The proposed method can detect the cracks on real concrete surfaces without being interfered by noises.	More images with more types of concrete damages under various conditions to be provided and added to the existing database to increase the adaptation and robustness of the proposed method.
(Xu et al., 2019)	Reduce the number of network parameters in concrete bridge crack detection	Crack detection model for concrete bridge based on the CNN, taking the advantage of Atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) module and depth	The proposed model achieved a detection accuracy of 96.37% without pre-training.	N/A

		wise separable convolution.		
(Zhang et al., 2018)	Develop an ImageNet-based pre-trained model to identify cracks and seal cracks in pavement images.	Training a DCNN to pre classify a pavement image, and a block wise thresholding method to segment the crack/sealed crack pixels and tensor voting–based curve detection to extract the crack/sealed crack.	The proposed approach accurately distinguishes cracks from sealed cracks and achieves very good detection performance.	N/A
(Yang et al., 2018)	Develop a novel approach for automatic detection and measurement of pixel-level cracked concrete structures.	Deep learning approach, named fully convolutional network (FCN). The architecture was composed of down sampling (conventional CNN layers) and up sampling (Deconvolutional layer).	The results show that FCN is feasible and sufficient for crack identification and measurement.	The accuracy is not as high as CrackNet.
(Cha et al., 2017)	Detect concrete cracks without calculating the defect features.	Vision-based method using a deep architecture of convolutional neural networks (CNNs) with sliding window techniques	The proposed method shows quite better performances especially in detecting thin cracks under lighting conditions.	Implementations of IPTs and CNNs, is incapable of sensing internal features due to the nature of photographic images.
(Wang et al., 2017)	Propose an approach to pavement cracking detection based on the learning from a large and diverse set of example data for a better consideration on the complexity and diversity of pavement surfaces.	CNN architecture with three convolutional and two fully connected layers for asphalt pavement crack recognition.	The proposed CNN is progressively improved, and the generalization is also enhanced. It is demonstrated that the trained CNN can achieve high accuracies 96.32 and 94.29% on training data and testing data respectively.	The proposed CNN recognizes cracks in image cells instead of detecting them at pixel level.

6. Deep learning-based concrete and steel cracks detection

Given the fact that this research focuses on analyzing major published articles for deep learning-based crack detection for both pavement and buildings, Table 2 presents the analysis of key articles that include application of using deep learning to detect cracks for buildings.

Table 2. Key articles for deep learning-based buildings and steel structures cracks detection

Author	Aim	Methodology	Findings	Limitation(s)
(Chow et al., 2020)	This study presents an AI-empowered inspection pipeline to streamline the visual inspection of the of concrete defects of civil infrastructure.	Using deep learning image-based inspection	The proposed CNN model can detect a wide range of defects under different environmental conditions. .	Limitations in detecting long and narrow cracks, identifying defects in patches of low contrast and sharpness, and misclassifying rough healthy concrete surfaces as spalled regions
(C. Zhang et al., 2020)	This study aims to develop a vision-based approach for detecting multiple surface damages in concrete highway bridges.	Using Real-time objection detection technique and You Only Look One (YOLOv3),	The developed algorithm can detect concrete crack, pop-out, spalling, and exposed rebar.	The dataset contains many small damages and complex background information, which could inhibit the algorithms' generalization and capacity.
(Dorafshan & Azari, 2020)	This study aims to investigate the feasibility of using deep learning models in detecting subsurface defects and overlay debonding from impact echo (IE) data.	Using one- and two-dimensional convolutional neural network (CNN).	Results show that the proposed 1D CNN was the most efficient in detecting debonding and subsurface defects.	Training dataset is limited.
(Fiorillo & Nassif, 2020)	This study presents a procedure that allows bridge engineers to estimate health index deterioration rates for bridge elements.	Using deep convolutional neural networks and NBI historic data.	The proposed approach better estimates NBI ratings from bridge element conditions.	Bridge elements data are still limited.
(Ghosh Mondal et al., 2020)	This study aims to assess multiple damage categories in reinforced concrete buildings due to an earthquake from visual data captured by the sensors mounted on the robots.	Using four different CNN architectures, namely, Inception v2, ResNet-50, ResNet-101, and Inception-ResNet-v2	Inception-ResNet-v2 was found to perform better (producing a MAP value of 60.8%) compared to Inception v2, ResNet-50 and ResNet-101. Also, it was found that the processing speed reduces with	The wide-ranging camera specifications leading to huge variations in image resolution and quality, which may potentially affect the performance of the proposed neural network-based approach.

			increase in accuracy.	
(Kim et al., 2020)	This study presents a methodology for automated bridge component recognition in 3D point cloud data.	Using deep learning in conjunction with subspace partition.	The proposed methodology is capable for robust and automated bridge component recognition from 3D point clouds of the full-scale bridges.	Unable to evaluate surface damages on the point cloud.
(Ali & Cha, 2019)	This study presents an approach to automatically detecting subsurface damage on steel bridge members.	By integrating infrared thermography (IRT) with the original deep inception neural network (DINN)	The developed method can accurately detect subsurface damage in those structural elements using thermal images and reduce computational costs.	The proposed method cannot differentiate the different types of damages.
(Kim & Cho, 2019)	This paper presents a crack assessment framework for concrete structures that detects and quantifies cracks.	Using Mask and region-based CNN (Mask R-CNN).	The proposed framework Detects most of the cracks 0.3 mm or wider and quantifies cracks with widths of 0.3 mm or more with errors less than 0.1 mm.	Cracks less than 0.3 mm widths show relatively larger error due image resolution.
(Liang, 2019)	This study presents a three-level image-based approach for post-disaster inspection of the reinforced concrete bridge.	Using convolutional neural network, object detection, and semantic segmentation.	Results show that all three-level deep learning models are very promising in terms of accuracies and robustness.	Small data set
(Li et al., 2019)	Develop a damage detection method to detect four concrete damages: cracks, spalling, efflorescence, and hole.	Using Fully Convolutional Network (FCN)	The proposed FCN was strong at detecting concrete damages: cracks, spalling, efflorescence, and holes, and showed low levels of noise.	The inability to detect the depth of damages.

7. Deep learning-based health structure evaluation

Table 3 shows the relevant studies that developed deep learning models to evaluate the structural health of existing buildigs, therefore, novice researchers can use mentioned limitations in these studies to develop solutions to bridge gap and foster the implemenattion of Artifitiial Intelligence (AI) for construction industry

Table 3. Deep learning-based structural health evaluations of buildings

Author	Aim	Methodology	Findings	Limitation
(Bae et al., 2021)	The study presents a deep super resolution crack network (SrcNet) to improve crack detectability during automated interpretation of digital images.	Using CNN-based Super Resolution (SR) technique combined with the semantic segmentation	Results show that the crack detectability of SrcNet was remarkably increased in terms of recall	Comparing with the crack detection results using raw digital images, positive false alarms were inversely increased
(Sajedi & Liang, 2021)	The study aims to leverage on deep Bayesian neural networks for vision-based structural inspections.	Using Bayesian inference and Monte Carlo dropout sampling. .	Bayesian inference can be an effective tool to make visual inspections using deep vision models.	Differences between the distribution patterns of entropy and MCSSD are observed.
(Dong et al., 2020)	This study proposes a method to achieve non-contact displacement monitoring for civil structures with less user involvement	Using deep learning-based full field optical flow methods.	Results show that the proposed method gives higher accuracy than the traditional optical flow algorithm.	Background clutter should be avoided to increase the accuracy of the flow prediction of the measurement.
(Gonzalez et al., 2020)	This study explores the potential of using a CNN to classify buildings according to their lateral load-resisting system	CNN in the dataset of nearly 10000 manually annotated photos at the street level.	The study results showed a precision of 93% and a recall of 95% when identifying nonductile buildings.	Misclassifications occur at the typology level.
(Kohiyama et al., 2020)	This study presents a method to detect unlearned damage patterns for structural health monitoring	Using the collective decision of support vector machines (SVMs).	The method can automatically recognize specific features for classifying damage patterns of a target structure with high accuracy.	The simulation model discordance.

(T. Zhang et al., 2020)	This study presents a new method for a challenging structural condition identification.	Based on a deep learning network architecture Alex-Net.	The results show that the proposed method is efficient and consistent in structural condition identification.	The sensor location is a key factor that may influence the algorithm performance.
(Huynh et al., 2019)	This study presents a quasi-autonomous vision-based for detecting loosened bolts in critical connections	Combination of regional convolutional neural network (RCNN)-based deep learning algorithm and the Hough line transform (HLT)-based image processing algorithm.	The results show that the proposed method can effectively monitor bolt-rotation of large, bolted joints and show a good performance in estimating as-of-now bolt-angle.	The proposed method can only provide the rotational angle of the bolt, not the preload loss happening in the bolt.
(Ni et al., 2019)	This study presents an efficient image-based structural damage detection and segmentation method at the pixel level for structural crack delineation.	By employing a feature pyramid network (FPN) and a generic pretrained CNN model, GoogLeNet CNN.	The results show that the proposed method can delineate cracks accurately and rapidly.	The delineation result can lose information of thin cracks in the images; whereas at the output with the relatively low F-measure values.
(Yu et al., 2019)	Develop a new quantitative physical fatigue evaluation method to evaluate the safety and health risks in different construction tasks arrangements.	By using deep learning algorithms, biomechanical analysis, and a physical fatigue model.	Results showed that the proposed method could assess the physical fatigue level of different construction task conditions such as site layout and the work-rest schedules.	In this study, the 3D motion estimation method cannot provide accurate 3D motion estimation when there are severe vision obstructions or under top-down perspectives.
(Atha & Jahanshahi, 2018)	This study aims to examine CNNs for corrosion detection of a sliding window over an image.	CNN architectures, ZF Net and VGG16, were evaluated and compared to three proposed CNNs, Corrosion7, Corrosion5, and VGG15, for corrosion detection.	CNNs outperforms the previous state-of-the-art corrosion detection approaches.	The type of corrosion cannot be identified, and the amount of corrosion cannot be measured.
(Pan et al., 2018)	This study presents an improved structural condition	Deep Bayesian Belief Network Learning (DBBN).	DBBN could achieve the high accuracy in structural diagnostics and	There are certain scatter points in prediction due to the high noise level.

	assessment for better decision making for the complex structures with uncertainties.		can could accurately determine the structural health state in terms of damage level.	
(Xu et al., 2018)	Identify and extract fatigue cracks from images containing complicated background on a steel structure surface s.	Deep learning network consisting of multiple processing restricted Boltzmann machine (RBM).	The results show that there exists optimal element size; that is, too small and too large element sizes both increase the reconstruction error and decrease the identification accuracy.	The capability of correct identification decreases for the images with low resolution.

8. Deep learning and Ground Penetrating Radar (GPR) to detect cracks

A few research proposed an integration of GPR and deep learning to detect construction objects and cracks, this enhanced the capabilities and accuracies of the CNN models. Table 4 shows studies that utilize deep learning in conjunction with GPR to detect objects.

Table 4. Deep learning studies based GPR for construction objects detection

Author	**Aim**	**Methodology**	**Findings**	**Limitation**
(H. Liu et al., 2020)	The study aims to detect and localise rebar in concrete using ground penetrating radar.	Based on the Single Shot Multibox Detector (SSD) model.	The developed SSD model can detect rebar with a high accuracy (90.9%.) in real time when a handheld ground penetrating radar system is operated at a walking speed	The study focuses only on rebar detection in concrete; it can be further used to detect other targets, such as subsurface pipes.
(Asadi et al., 2020)	This study aims to develop a computer vision-based rebar detection chain for automatic processing of concrete bridge deck GPR images	Fined-tuned Histogram of Oriented Gradients/ Multi-Layer Perceptron based binary image classifier which is trained on URIGPR dataset and then applying a post-processing algorithm	The obtained experimental results indicate that for classification of grayscale GPR B-scan images a HOG/MLP classifier outperforms all studied CNN models on URIGPR dataset.	Some False Negative detections of hyperbola pattern in highly deteriorated regions are observed.

		for removing false detections.		
(J. Zhang et al., 2020)	This study aims to automatically detect and localize the moisture damage area from GPR B-scan image to make a fast and precise maintenance decision.	Using mixed deep convolutional neural networks (CNN) including ResNet50 network, for feature extraction, and YOLO v2 network, for recognition.	The proposed detection CNN model shows F1 score (91.97%), Recall (94.53%) and Precision (91.00%), showing that deep learning is reliable in detecting and localising moisture damages in asphalt pavements.	To further use the latest deep framework to achieve greater improvement in Precision and Recall.
(Lei et al., 2019)	This study aims to present an automatic scheme for buried objects detection and localization.	Combining a trained deep learning framework — Faster R-CNN, preprocessing method, DCSE, and CTFP metho	Comparison with traditional GPR shows that this proposed scheme is more accurate and robust in terms of real-time detection and localization of targets in the experiments.	here is a redundant detection obtained by Faster R-CN

9. Discussion, Significance and Limitation

This study provides a comprehensive review in terms of using deep learning to detect a wide range of distresses for pavements and buildings. The papers categorized the utilization of deep learning to two main themes, which are deep learning for pavement distresses and deep learning to evaluate structural health of buildings. The findings are promising, and it has been regonized that deep learning has been successfully implemented to detect a wide range of cracks with a very high level of accuracy. For instance, Elghaish et al. (2021) developed a CNN model that can detect and classify a wide range of cracks with an accuracy more than 97% and three optimization algorithms were compared in this study to maximize the level of accuracy. With respect to the area of deep learning to evaluate the structural health, there are a few studies compared to pavement's studies and the majority of studies focus on developing solutions to detect and evaluate specific structural elements (e.g., fatigue cracks in steel structures, detect loosened bolts, detect corrosion of a sliding window) rather than presenting an integrated evaluation solution-based deep learning.

It was recognized based on the numerous studies that were reviewed that there is a common limitation for most of studies “database size”. Thus, further research is needed to develop solutions that can accommodate large size databases and ensure the accuracy of the proposed model in the real-life settings. Moreover, the developments should focus in providing a comprehensive tool, for example, articulating a framework to show the best data collection method, different CNN models according to the type of cracks/distresses and the way of presenting the outcome of the analysis of collected images. This can lead to an integrated maintenance system for highways, steel and concrete buildings.

The utilization of deep learning to assess the health of steel and concrete surfaces was significantly improved, particularly, identifying fatigues, detecting later-load resisting systems, automatically collecting structural information to determine conditions of the complex structures with uncertainties and predicting the damage pattern. However, all attempts did not consider the entire process of data collecting, data analysis-based deep learning CNN models and maintenance decision making system based on the outcome from the deep learning analysis.

Different technologies have been integrated into deep learning to enhance its accuracy (e.g., CNN models), as well as, collecting reliable data (e.g., images of distresses). One of these technologies is GPR that was employed in some studies to (1) detect rebars locations and numbers in the concrete, (2) detect and localize moisture damage in pavements, (3) explore buried objects.

Given, there are many workable deep learning models were developed, however, in order to foster it is implementation, the deep learning models should be integrated into other technologies such as BIM, Internet of Things and Immersive technologies. An example of a solution that can be integrated into deep learning is, Sheikhkhoshkar et al. (2019) proposed a 4D BIM-based solution to plan for the concrete joints layout and such model can be integrated into deep leaning to provide an integrated solution.

This research adopted a structured technique that relies on analyzing all articles in the same way to present the focus of study, employed methods, key findings and limitations and thus, allows future researchers to easily find the deficiencies of each tool, how other researchers contributed to solve it, and recommendations to develop further solutions/enhance existing tools. Moreover, this paper provides a solid knowledge base to educators and students that want to adopt deep learning in their curriculum through deciding the optimal approach to be used in their laboratories as well as enabling students to compare between traditional distresses approaches and deep learning or comparing deep learning models.

Due to having a wide range of distresses and this varies from a case to another. Therefore, this article proposes that additional research is needed to compare a wide range of pre-trained deep learning models to identify characteristics that can detect and classify a wide range of distresses precisely, subsequently, more new designated CNN models can be developed based on the characteristics of available data. Moreover, testing each CNN model against different optimization algorithms to enhance the accuracy of CNN models.

Given, the methodology of this research was applied to specific point, which is the utilization deep learning-based crack detection and articles were analyzed according to their focus of study, methods, contribution/recommendations, and limitations. This structured analysis way provided a deep overview of strengths and weaknesses of employing such technology to detect and classify distresses. As such, another study is recommended to be conducted using the same structured critical analysis method to explore deep learning in other application such as construction site health and safety, equipment detection, energy performance management, etc.

10. Conclusion

This paper provided a state-of-the-art review on the applications of different deep learning techniques to detect and assess distress in both pavements and buildings. Several deep learning tools, techniques and algorithms have been investigated. Those techniques include but are not limited to ANN, CNN, SVM, DBBN, DINN, GPR, etc. Furthermore, applications of those techniques on detecting cracks in pavements and buildings have been discussed and analyzed.

Based on the state-of-the-art review, the future of applying deep learning algorithms as a replacement for manual inspection has shown promising results. The key findings could be summarized as follows: (1) training a customized model with a small amount of data showed high detection accuracy in concrete structures and pavement; (2) quality and amount of data are paramount to enhance the accuracy of cracks' detection and assessment; (3) SVM is capable of detecting data with unrelated patterns; (4) quality of images (e.g. image resolution, lighting conditions, etc.) impacts the accuracy of cracks' detection; and (5) accuracy of the existing models along with the huge time and resources' savings are the key benefits of adopting those algorithms over the manual systems.

Even though, the research has shown promising results for the future of applying deep learning on cracks detection, further research is required to analyze the setup, implementation, and operational costs. Moreover, the optimal frequency of capturing the data shall be investigated to ensure timely detection of the cracks and minimize the operational and data storage costs. Finally, further analysis is required to select the ideal deep learning algorithm while taking into consideration the structure type, available data, etc.

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Comment: 1. The author(s) have stated in their response that "We have also double-checked limitations to avoid subjective judgement."

I'd recommend adding the same statement to the methodology section.

2. The author(s) also have stated in their response that "Authors mentioned [the geographical allocation of publications] in the methodology as an indication for future researcher to know the progress of research in this area over the world."

I'd recommend adding the same statement to the paragraph that explains the figure.

Response: Thanks for your comment: Authors have added two statements as recommended.