Deep Learning Algorithms for Identifying Defects in Concrete Structures

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Abstract - The presence of cracks is often the first sign of deterioration in concrete pavement. Detecting and addressing these cracks early on is crucial for effective pavement maintenance. Deep learning algorithms, continuously advancing with improvements in computer hardware, offer a more accurate and automated approach to crack detection compared to traditional digital image processing methods. This has sparked interest in researching concrete pavement crack images, as it promises enhanced resilience. Among deep learning techniques, convolutional neural networks (CNNs) have been specifically developed for automatic analysis of concrete surface photographs in crack diagnosis applications. Despite the high accuracy claimed by deep learning-based systems, it is crucial to consider an alternative perspective that highlights the neglect of challenges related to obtaining high-quality images. the limitations of manual inspections, which are time-consuming and subjective, by proposing an alternative approach that streamlines the process. By reducing the reliance on subjective experience, this approach improves efficiency and minimizes the potential for errors in detecting visual indications of stress, wear, and strain, such as cracks and depressions. Such indications, if left unattended, can gradually lead to failure or collapse, especially when they occur in critical areas like load-bearing joints.

Keywords - Deep Learing (DL), Convolution neural networks (CNN), Artificial neural networks (ANNs).

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INTRODUCTION

Concrete structures, including bridges, beams, columns, and highways, face substantial levels of stress and strain due to various factors such as cyclic loading, temperature changes, and weathering. Consequently, cracks can develop and propagate within these structures, sometimes interconnecting and growing larger over time. Timely detection of such failures in concrete structures is of utmost importance, especially in offshore and onshore environments, bridges, concrete pillars, and concrete pipelines. Early identification allows for the implementation of preventive measures to mitigate the risk of failures, ensuring the protection of both assets and lives. By proactively identifying and addressing potential issues, catastrophic failures can be averted, resulting in significant savings in terms of financial resources and human safety.

Concrete structures can be assessed for cracks using either invasive or non-invasive methods. Invasive techniques require specialized equipment like infrared light, thermal testing, ultrasonic techniques, and laboratory testing of concrete samples. However, these invasive methods are often time-consuming and intricate, necessitating the involvement of structural experts to analyze and interpret the collected data. The outcomes obtained from these techniques are reliant on human interpretation and expertise.

Alternatively, non-invasive techniques that utilize digital image analysis of concrete structures have become increasingly popular due to advancements in imaging capabilities and computational power. Over the past few decades, more than 50 articles have been published, focusing on the identification of concrete cracks and discussing various pre-processing and post-processing techniques. This comprehensive overview of these methods provides valuable insights into their strengths and weaknesses, helping to understand their effectiveness and potential applications.

In the past few years, there has been a growing interest in utilizing deep learning techniques, specifically artificial neural networks (ANNs) and convolutional neural networks (CNNs), for automatic processing of images to identify cracks and failures in concrete structures on land. Thanks to advancements in artificial intelligence and deep learning technologies, several applications have emerged that employ CNN-based neural networks for identifying surface cracks in concrete. Many of these methods have demonstrated a high level of accuracy in classifying cracks, showcasing the potential of deep learning in this field. The majority of the published research on these approaches spans the last decade.

For example, in a conference paper published in 2011, a backpropagation neural network was trained using 105 concrete images and tested on 120 new images. The network achieved a recognition rate of 90% for crack images and 92% for non-crack images. Another methodology was presented that utilized object detection techniques, using over 205 images with a resolution of 256x256, resulting in a high accuracy of 96% in detecting cracks. Furthermore, an image segmentation method was employed in another study, enabling automatic peak detection and identification of concrete cracks. These advancements highlight the potential of deep learning in enhancing crack detection and identification in concrete structures.

Cracks in buildings are a common and widespread issue experienced worldwide. These cracks occur when the stress exerted on building components surpasses their strength. Stress on building components can arise from external factors such as dead and live loads, wind, seismic forces, or foundation settlement. It can also be internally induced by temperature fluctuations, moisture changes, and chemical reactions. Cracks not only detract from the aesthetic appearance of buildings but also compromise the integrity ofwalls, jeopardize the safety of the overall structure, and reduce its long-term durability. Addressing and mitigating the effects of cracks is crucial for maintaining the structural and functional integrity of buildings.

There is a need for sustainable

1. Concrete structures form the backbone of our infrastructure, supporting buildings, bridges, roads, and other vital components of modern society. However, these structures are susceptible to various defects that can compromise their integrity and pose safety risks. Detecting and identifying these defects in a timely and accurate manner is crucial for effective maintenance and ensuring the long-term durability of concrete structures.

2. Deep learning algorithms have emerged as a promising solution for automated defect identification in various fields, including computer vision and image analysis. These algorithms leverage the power of artificial neural networks to learn intricate patterns and features directly from large datasets. By training deep learning models on extensive collections of concrete structure images, it is possible to develop algorithms that can accurately recognize and classify different types of defects.

NEED OF THE STUDY

In this study, we aim to develop and investigate deep learning algorithms specifically tailored for identifying defects in concrete structures. We will explore various deep learning architectures, such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), or their combinations, to determine the most effective approach. Furthermore, we will evaluate the impact of different network configurations, optimization techniques, and data augmentation methods on the performance of the algorithms.

Deep learning algorithms for defect identification in concrete structures holds significant implications for infrastructure maintenance and safety. By automating the process, we can expedite defect detection, improve the accuracy of identification, and enable proactive maintenance strategies. This research seeks to contribute to the advancement of deep learning techniques in the field of civil engineering, providing valuable insights and tools for enhancing the assessment, management, and preservation of concrete structures.Proper use of demolished construction material: Demolished construction materials often end up as waste, contributing to the overall waste management problem. By studying and identifying the potential of these materials for reuse in new construction projects, we can minimize waste and promote resource efficiency.

LITERATURE REVIEW

The topic “Identification of defect in concrete structure using deep learning” was taken under study as it is the need of structural cracks and it is trending topic under research. Many researcheshave already been identification of crack length, width and classification of structural cracks. Some of the research literatures are reviewed in this chapter to take a brief glance and comprehensive scenario to work further with.

The paragraph discusses a study that employs the self-consistent method to calculate the elastic moduli of bodies that contain randomly distributed flat cracks. The study investigates both cracked bodies with fluid present in the cracks and those without. The authors provide a broad overview of general concepts that are applicable to cracks of any shape and provide explicit derivations and numerical results specifically for elliptic cracks. They also identify parameters that can be used to extend the findings from elliptic cracks to other types of convex crack shapes. Additionally, the study presents geometrical relationships that involve randomly distributed cracks and their traces on cross-sections. The overall aim of the study is to offer a comprehensive understanding of the behavior of cracked bodies and provide valuable insights for further research and analysis in this field.

The paragraph introduces a method for calculating the effective moduli of elastic solids that contain a regular pattern of rectangular cracks. The method involves analyzing a unit cell and expanding the displacement vector to a second order based on the distances from the centerlines. By considering equilibrium equations and incorporating continuity conditions for displacements and tractions, a system of equations for the elastic field variables is derived. The elastic internal energy is then determined, enabling the calculation of the desired effective moduli for the cracked body. The method is applied to predict stiffness loss in various materials, such as isotropic solids with cracks, unidirectional composites, and cross-ply laminates with cracks. This approach provides valuable insights into the behavior of cracked materials and contributes to the understanding of mechanical properties in structures containing cracks.

Cracks observed on concrete surfaces are crucial indicators of structural degradation, and their timely detection is vital for maintenance purposes to prevent severe environmental damage. Currently, the widely accepted method for crack detection is manual inspection, where specialists visually assess cracks, sketch them, and record details about their irregularities. However, this approach is subjective and lacks objectivity in quantitative analysis, as it heavily relies on the expertise and experience of the specialist.

To overcome this limitation, an alternative solution is proposed: automatic image-based crack detection. The existing body of literature presents various image processing techniques that can automatically identify cracks and estimate their depth. In this research, a comprehensive survey is conducted to identify the research challenges and accomplishments in this field. Fifty research papers related to crack detection are reviewed and analyzed, taking into consideration aspects such as image processing techniques, objectives, accuracy levels, error levels, and the image datasets used.

Through this review, several research issues are identified, which can serve as guidance and inspiration for further advancements in the field of crack detection. This comprehensive overview aims to contribute to the development of more objective and accurate methods for crack detection, reducing reliance on manual inspection and improving maintenance practices for concrete structures.

The objective of this study was to develop an image analysis technique utilizing deep learning for the detection of cracks and analysis of their characteristics, such as length and width, in images of small-scale facilities. The proposed method consists of three stages in the image processing pipeline. In the first and second stages, two-dimensional convolutional neural networks are employed for crack image detection, including classification and segmentation tasks. To enhance the performance of crack detection, a hierarchical feature learning architecture is incorporated into the deep learning network. Once the cracks are detected using the deep learning approach, the third stage utilizes thinning and tracking algorithms to analyze the length and width of the cracks in the image. The effectiveness of the proposed method was evaluated by testing it on various crack images with known labels. The results demonstrated the method's ability to achieve accurate crack detection and reliable measurements of crack dimensions.

In an effort to partially replace human-conducted onsite inspections for detecting defects in civil infrastructure, various image processing techniques (IPTs) have been implemented. These IPTs primarily manipulate images to extract features related to defects, specifically cracks in concrete and steel surfaces. However, the widespread adoption of IPTs faces challenges due to the diverse real-world situations encountered, such as changes in lighting conditions and the presence of shadows.

To address these challenges, this article introduces a vision-based method that utilizes a deep convolutional neural network (CNN) architecture for concrete crack detection, without the need for explicitly calculating defect features. By leveraging the automatic feature learning capabilities of CNNs, the proposed method eliminates the requirement for additional IPTs to extract features. The CNN is trained on a dataset consisting of 40,000 images with resolutions of 256 × 256 pixels, achieving an impressive accuracy rate of approximately 98%.

To handle images larger than 256 × 256 pixels, the trained CNN is combined with a sliding window technique for efficient scanning. The robustness and adaptability of the proposed approach are tested on a set of 55 images with resolutions of 5,888 × 3,584 pixels, which are obtained from a different structure that was not used during the training and validation process. These images encompass a wide range of conditions, including strong light spots, shadows, and very thin cracks.

Comparative studies reveal that the proposed CNN-based approach outperforms other existing methods, demonstrating its effectiveness in detecting concrete cracks in realistic scenarios. This highlights the potential of the approach to enhance the efficiency and accuracy of defect detection in civil infrastructure, ultimately reducing the reliance on manual inspections.

This article introduces a novel approach to autonomous concrete crack detection utilizing deep learning and hybrid images. By combining vision and infrared thermography images, the hybrid images offer enhanced crack detectability while reducing the occurrence of false alarms. This technique proves to be particularly effective for inspecting large-scale concrete structures such as bridges and dams. It employs an unmanned vehicle-mounted hybrid imaging system equipped with a vision camera, an infrared camera, and a continuous-wave line laser.

Traditionally, crack identification in industrial fields has relied on expert-dependent decision-making, which can be burdensome, time-consuming, and unreliable. As the size of the concrete structure increases, the need for automated decision-making becomes more desirable. The proposed technique addresses this need by leveraging transfer learning with a well-trained deep convolutional neural network, specifically Google Net, to achieve automated crack identification and visualization. This approach combines the benefits of hybrid images with the efficiency and reliability of automated decision-making.

Experimental validation of the proposed technique is conducted using a laboratory-scale concrete specimen featuring cracks of varying sizes. The results demonstrate the automatic visualization of both macro- and micro-cracks while minimizing the occurrence of false alarms. This showcases the effectiveness of the approach in autonomously detecting and visualizing concrete cracks.

Maintaining the integrity of reinforced cement concrete structures involves monitoring the health of the concrete, which includes detecting defects like cracking and spalling, particularly in structures affected by fire. Traditionally, this process relies heavily on human inspection, which is subjective and relies on the expertise of the inspectors. To address this limitation, a novel automatic crack detection method based on deep learning is proposed. Deep learning is a powerful technique within the field of computer vision. The proposed method utilizes a U-Net architecture with an encoder and decoder framework, enabling accurate pixel-wise classification for thermal crack detection. A Binary Cross Entropy (BCA) based loss function is chosen as the evaluation function. The trained U-Net model is capable of detecting both major and minor thermal cracks across various heating durations. This U-Net crack detection method is innovative and can be applied to identify thermal cracks on concrete structures exposed to fire. A comparison with other state-of-the-art methods demonstrates the accuracy of the proposed approach, achieving an Intersection over Union (IOU) score of 78.12%.

This paper introduces a customized convolutional neural network (CNN) specifically designed for detecting cracks in concrete structures. The proposed method is compared to four existing deep learning methods, considering factors such as the size of the training data, data heterogeneity, network complexity, and the number of training epochs. The performance of the proposed CNN model is evaluated and benchmarked against popular pretrained networks, including VGG-16, VGG-19, ResNet-50, and Inception V3 models. The evaluation process involves eight datasets of varying sizes, which are derived from two publicly available datasets. Various aspects are considered during the evaluation, such as computational time, crack localization results, and classification measures including accuracy, precision, recall, and F1-score. The experimental results highlight the significant impact of training data size and heterogeneity on the performance of the models. All models demonstrate promising performance when trained on limited amounts of diverse training data. However, as the size of the training data increases while the diversity decreases, the generalization performance of the models deteriorates, leading to overfitting. These findings emphasize the importance of striking a balance between training data quantity and diversity to achieve optimal performance in crack detection models.

The proposed study aims to assess and compare the performance of a customized convolutional neural network (CNN) and the VGG-16 model with other existing methods for crack detection in concrete structures. The evaluation encompasses several factors, including classification accuracy, localization accuracy, and computational time, with a particular focus on a limited dataset. The results of the study reveal that both the customized CNN and VGG-16 models outperform the other methods in terms of classification accuracy, localization accuracy, and computational time. These findings indicate that the customized CNN and VGG-16 models exhibit superior capabilities for detecting and localizing cracks in concrete structures.Based on these results, it can be concluded that the customized CNN and VGG-16 models offer enhanced performance and efficiency in crack detection, making them promising options for concrete structure assessment and maintenance.

The conventional methods for identifying defects in concrete structures heavily rely on manual inspections performed by trained professionals. Although these inspections can be effective, they are often laborious, time-consuming, and prone to human error. Moreover, such inspections may fail to detect subtle or concealed defects, which can potentially lead to serious consequences if left undetected. Hence, there is an increasing demand for automated and reliable approaches to detect and classify defects in concrete structures. The findings of this study indicate that the proposed customized convolutional neural network (CNN) and VGG-16 models show promise as effective and efficient tools in addressing this demand. These models have the potential to automate the defect detection process, offering benefits such as improved accuracy, faster analysis, and reduced dependence on manual inspections. By utilizing these models, the identification of defects in concrete structures can be enhanced, leading to more comprehensive assessments and proactive maintenance strategies.

OBJECTIVES

Objectives of the project are as follows:

1. To Identify Concrete Crack Detection System.

2. To Utilize Suitable Deep Learning Algorithm For Concrete Crack Detection.

3. To Modify The Algorithm For Classification of Damage Levels.

METHODOLOGY

Methodology with respect to each objective is briefly given below:

1. To Identify Concrete Crack Detection System.

Traditionally, determining the width of cracks in concrete structures has relied on manual and non-systematic approaches, which involve collecting information and making judgments based on personal justifications. These methods are time-consuming and prone to human errors. Recognizing these limitations, there has been an increasing focus on developing new approaches for crack detection and monitoring in recent years. These emerging methods aim to provide more efficient and accurate techniques for measuring crack width in concrete structures, reducing reliance on subjective judgments and improving overall reliability.

2. To Utilize Suitable Deep Learning Algorithm For Concrete Crack Detection.

Cracks serve as a critical indicator for assessing the extent of damage in concrete structures. Nonetheless, traditionalncrack detection algorithms are often complex to implement and lack strong generalization capabilities. Existing crack detection algorithms based on deep learning primarily rely on window-level techniques, resulting in low pixel precision. To address these limitations, the objective of this research is to enhance the algorithm by incorporating modifications that allow for differentiation between different levels of damage in concrete structures. The aim is to develop a more accurate and precise crack detection approach that can effectively distinguish varying degrees of damage within the concrete.

3. To Modify The Algorithm For Classification of Damage Levels.

Existing techniques for crack detection in concrete structures generally suffer from significant limitations, such as low accuracy and efficiency. However, with the advancement of convolutional neural network (CNN) methods, digital image processing-based crack identification has shown improved performance. Many approaches utilize single classifiers to detect cracks with high accuracy. However, these classifiers may overlook random fluctuations in the training dataset, resulting in an overfitting phenomenon that negatively impacts the final output. In order to overcome these limitations, there is a need for more robust and sophisticated approaches that can effectively address the challenges posed by crack detection in concrete structures.

RESULT

1. To Identify Concrete Crack Detection System. ANNEXURE

```
clc,clear,close all;

  % Upload image from folder named "cracks"
```

```
[filename,pathname] = uigetfile('crack.jpeg','C:\Users\Hp\Documents\crackImages');im1 = imread([pathname,filename]);

scale = 600/(max(size(im1(:,:,1))));

im1 = imresize(im1,scale*size(im1(:,:,1)));

% % Image resize [m,n,~] = size(im1);

        Red = im1(:,:,1);

        Green = im1(:,:,2);

        Blue = im1(:,:,3);

        %Get histValues for each channel[yRed, x] = imhist(Red); [yGreen, x] = imhist(Green); [yBlue, x] = imhist(Blue);

        %Plot them together in one plotfigure(3)

        plot(x, yRed, 'Red', x, yGreen, 'Green', x, yBlue, 'Blue');title('Histogram of Cover image ');

 %PLEASE INSERT A VALUE!

% USE 0 IN CASE YOU DON'T WANT THE BRIGHTNESS TO CHANGE

br = inputdlg('Enter the increased/decreased amount of brightness');Br = str2double(br)

im = im1 + Br;imtool(im);

%% Image processing

% Convert image from RGB to gray scale I = rgb2gray(im);

        Red = I(:,:,1);

        %Get histValues for each channel[yRed, x] = imhist(Red);

         [yGreen, x] = imhist(Green); [yBlue, x] = imhist(Blue);

        %Plot them together in one plotfigure(4);

        plot(x, yRed, 'Red', x, yGreen, 'Green', x, yBlue, 'Blue'); title('Histogram of Cover image of changed intensity image ');

figure(2) subplot(1,2,1)imhist(I) xlim([0,250]);

title('Histogram before enhancement')imtool(I)

% Image enhancment

% First) 9*9 low pass filter [f1,f2]=freqspace(size(I),'meshgrid');D=100/size(I,1);

% display('D');

% D

% display('Size');

% size(I,1)

% display('F1');

% % f1

% display('f2');

% f2

% LPF = ones(9);r=f1.^2+f2.^2; for i=1:9

    for j=1:9

        t=r(i,j)/(D*D);

        LPF(i,j)=exp(-t);

    end

end

% LPF

% Second) applying filter Y=fft2(double(I)); Y=fftshift(Y); Y=convn(Y,LPF); Y=ifftshift(Y); I_en=ifft2(Y);

% Third) blurr image I_en=imresize(I_en,size(I)); I_en=uint8(I_en); I_en=imsubtract(I,I_en);

I_en=imadd(I_en,uint8(mean2(I)*ones(size(I))));

subplot(1,2,2)imhist(I_en) xlim([0,250]);

title('Histogram after enhancement blur') imtool(I_en)

% Segmentation of image

level = graythresh(I_en); % Calculate threshold using Otsu's method

BW = ~im2bw(I_en,level); % Convert image to binary image using thresholdimtool(BW)

disp("The threshold value is: ")disp(level)

% Removing noise and conecting image BW1 = BW;
```

```
BW2 = BW1;

%BW1 = imdilate(BW1,strel('disk',i));   % dilate image

% BW1 = bwmorph(BW1,'bridge',inf);                %
connecting close parts

% BW1 = bwmorph(BW1,'diag',inf);

% BW1 = bwmorph(BW1,'close',inf);

% %imtool(BW1)

% BW1 = imfill(BW1,'holes');

 % filling small spaces

% se = strel('line',11,90);

% BW1 = imdilate(BW1,se);

% BW1 = imerode(BW1,strel('disk',i-1));

 % erode image

%imtool(BW)

tmp = bwareafilt(BW1,1);                     % get
size of biggest connected shape tmp =
fix(0.05*sum(sum(tmp)));                     %
size considered noise

BW1   = bwareaopen(BW1,tmp);                 %
remove isolated pixelsimtool(BW)

CC = bwconncomp(BW1);

if CC.NumObjects<1;end                 % break the
loop at convergence
```

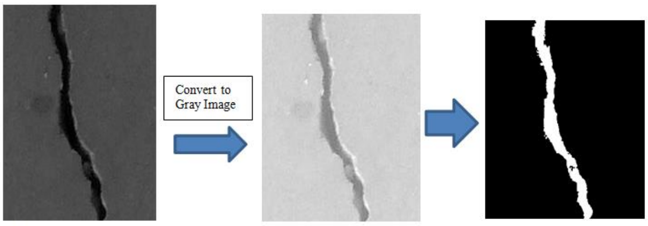

Fig.1 original image Binary Image Segmentation Image

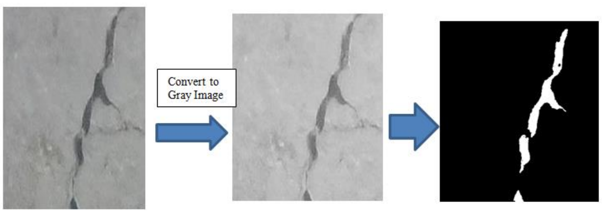

Fig. 2 original Image Binary Image Segmentation Image

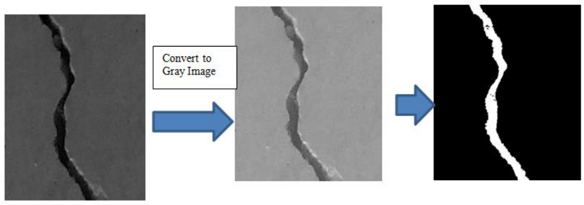

Fig. 3 original Image Binary Image Segmentation Image

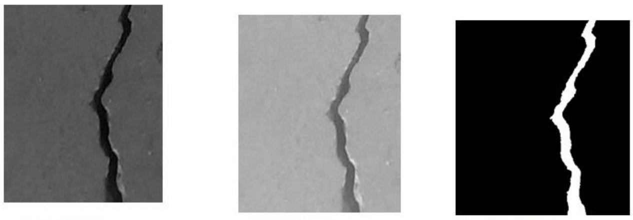

Fig. 4 original Binary Image Segmentation Image

CONCLUSION

1) The concrete crack detection system depends on factors such as the scale and complexity of the structure, the desired level of accuracy, and the available resources. A combination of visual inspection, NDT techniques, automated crack detection systems, and sensor-based monitoring can provide a comprehensive and reliable approach to identify and monitor cracks in concrete structures, ensuring their safety and longevity.

2) By considering these factors and conducting thorough research on the available crack detection systems, it becomes possible to identify a system that meets the specific requirements of the project while providing accurate and reliable results for effective crack detection in concrete structures.

3) A suitable deep learning algorithm can be effectively utilized for concrete crack detection, providing accurate and reliable results for maintaining the integrity and safety of concrete structures.

4) The concrete crack detection task, a suitable deep learning algorithm can be utilized effectively, providing accurate and reliable crack detection capabilities for concrete structures.

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