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Bridge Crack Detection Based on Convolutional Neural Networks

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ABSTRACT

Identifying cracks in bridges and determining the status of bridges are primarily manual labor-intensive tasks. Bridge inspection by human experts has some problems, such as the difficulty to physically inspect all portions of the bridge and the reliance on the expert knowledge of the bridge inspector as the sole source of information. Moreover, sufficient training of the human resource is required, and the overall cost of the solution is not cost effective. Data obtained from newspapers, web portals, and other sources indicates that there have been reports of many fatalities in the state of Maharashtra as a result of bridge and civil structural collapses, according to the data. Most of these incidents were reported to have occurred as a result of ignorance and lack of maintenance, which was caused by the high cost of human resources and manual inspection, as noticed in the majority of the incident reports. Using wavelet-based image characteristics in conjunction with CNN, this research provides an automatic bridge inspection method that can detect cracks in bridge photographs without the need for human intervention. In order to develop a system that can detect cracks in bridges, various bridge crack photos are collected and used as samples. A two-stage technique is used, with the first stage determining whether or not an image should be subjected to a pre-processing phase based on the image's attributes. The scanning and processing of an image should be done in accordance with the characteristics of the image. Wavelet characteristics are extracted from the image later in the second stage using a sliding window-based technique, which is described in detail below. The converted image contains the extracted features, which can be used to compare the input image with several images from a dataset, as seen below. The Convolution Neural Network Algorithm aids in the extraction of image features and the conversion of the image to grey scale. It is a type of neural network algorithm. The model is developed for the identification of bridge cracks, and it is stimulated and trained using the MATLAB programming language. It is possible to determine the crack classification of a bridge.

Keywords : Convolution Neural Network, Image Processing, Feature extraction

I. INTRODUCTION

Physically inspecting bridge conditions might become impossible owing to a variety of issues, including the bridge's physical surroundings, a lack of specialist knowledge, and a lack of human resources. The maintenance and repair of bridges necessitates the adoption of prompt decisions in this regard. Many bridge authorities rely on Bridge Management Systems (BMSs) to handle their routine inspection information and to make decisions about what repair services to provide as a result. As sophisticated instruments and powerful computers have become more widely available, there has been an increase in the number of attempts to automate bridge inspections in recent years. Unfortunately, the approaches that were offered were not entirely capable of addressing the difficulties associated with crack detection. One of the most challenging aspects of automatic crack identification algorithms is dealing with changeable lighting circumstances, random camera/view angle selection, and varying quality of bridge photos. Furthermore, we discovered that IOT-based crack detection becomes even more difficult when the backdrop texture varies on a random basis, making segmentation of background and foreground elements extremely difficult to do. According to this research, a non-trivial technique for addressing the issues listed above is proposed and demonstrated to be effective. This technique is divided into two stages. Initially, the image is classified as either a 'complex image' or a 'simple image' based on the features of the pixel values in the 'R', 'G', and 'B' channels that are analysed in the initial analysis. If the image is classified as a 'complex image,' we must do a pre-processing step; otherwise, the image is processed straight for feature extraction without any further processing. Texture analysis–based features are extracted from the picture region beneath a non-overlapping sliding window, which is used to separate the image region from the sliding window. In a subsequent step, those characteristics are transmitted to a CNN classifier, which determines if a fracture exists in the region beneath the sliding window or not.

The collapse of the bridges resulted in a large number of casualties and significant property damage [1]. The need of frequent inspection and repair of bridges cannot be overemphasised. Automatic detection of bridge disease algorithms have been increasingly popular in recent years, and are being utilised more and more for bridge inspection. These algorithms eliminate the considerable danger and hassle associated with manual detection during the course of the task.

The cracking of bridges is one of the most common diseases that affect bridges [2]. Many academics have conducted research on automatic crack detection algorithms in recent years [3-5], and the results have been published. In general, these algorithms can be divided into two categories: those based on classic digital image processing and those based on artificial neural networks. The model developed by (Adhikari) is based on digital image processing and is integrated [6]. Crack quantification, neural networks, and a 3D visualisation model are used to check the visual simulation of an on-site inspection in his model. Zhang [7] suggested an image mosaic algorithm based on the extraction of ORB features from images. Texture analysis in millimetres is provided by (Ankur Dixit) utilising morphological component analysis after sparse coding and sobel filtering [8] after sparse coding and sobel filtering. However, deep learning is also used in the identification of bridge cracks, which is another application. Pavement fracture identification was carried out by (Zhang Lei) using a deep neural network structure consisting of four convolutional layers[9]. The accuracy of deep convolutional neural networks was also demonstrated by the author, who claimed that it reached 95%. The outcome is superior to that of support vector machine (SVM) and Boosting combined. To detect cracks, the authors (YJ Cha) propose a layout that combines the convolutional neural network (CNN) with the sliding window technique. This procedure lowers the impact of cracks created by image cutting on the final product. The author compares his concept to classic edge detection methods such as canny and sobel.

The cracks are classified in two distinct ways by the algorithms described above, but each technique has its own limits. Traditional digital image processing methods do not have a flawless algorithm for removing noise from images, which is a well-known difficulty in the field of traditional digital image processing methods. There is no way that a denoising algorithm can be effective on all photos, no matter how complicated it is. However, because of its high adaptability, artificial neural networks (ANN) may be able to tackle the problem. The above-mentioned ANN algorithms are capable of correctly classifying the crack images with an accuracy of 90 percent. However, they make mistakes with the typical photos as well, with a 30 percent error rate.

Towards resolving these issues, this paper proposes a new crack detection and measurement method based on convolutional neural networks and traditional image processing. There are number of various application in which CNN has shown excellent results like, human behaviour prediction [10], for driver fatigue detection [11], for disease prediction [12], analysis of social media users [13] etc. This method achieves high accuracy in crack detection also and pixel-level parameter measurement while maintaining low computational complexity. The following are the specifics of our contributions: 1.Image preparation is accomplished through the use of semantic segmentation. It is capable of extracting bridges from the background. 2. In order to classify the crack image with higher accuracy and faster speed than previously, the VGG network structure is referenced and the data set is changed to account for this. 3. Reconstruct the image using the feature maps that were recovered earlier, which were then utilised to measure the length of the fracture with pixel-level accuracy.

II. BRIDGE CRACK DETERCTION

Figure 1 depicts the organization culture of object recognition and variable detection using a convolutional neural network for classification and detection of parameters. The drone is responsible for taking the initial image. A large amount of redundant information is present in this shot because of the complicated context of the bridge and the poor shooting conditions. To obtain the primary part of the bridge, the original image is first processed through a semantic image segmentation layer, such as a full convolutional network (FCN), before being passed through another layer of image segmentation. The image processed by FCN is divided into small image blocks of 224224 pixels in size, which are then categorised by CNN using a computer vision algorithm. Last but not least, the rebuild picture matched by the feature map is designed in such a way that the fracture parameters (length) may be obtained by passing through the forecast layer.

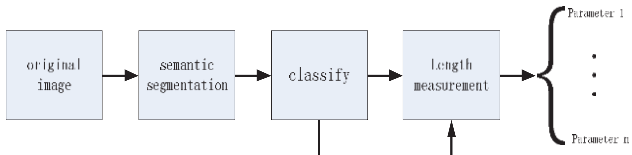


Fig 1.CNN-based image classification and parameter detection process

1.1 Semantic Segmentation

Semantic segmentation is the basic task of computer vision. It is a pixel-level classification task. The task of semantic segmentation is to divide the picture into different semantic scenes in units of pixels and fill with different colors to distinguish them. As one of the classical semantic segmentation networks, FCN can accomplish the task of semantic segmentation.

The original image of the bridge crack used in this paper is taken by the drone. The original images are often included useless scene due to the shaking of the drone, the integrity of the image and the artificial uncertainty. Redundant images, such as water surface, plants etc., have different colors and textures. They will cause interference in the detection of crack images which dominated by gray. The original images firstly go through the FCN for semantic segmentation before classify them. And the complete image of the bridge crack is extracted as the region of interest while the other part is the background region. We remove the redundant image, fill the background area with the average color of the interest region to ensure the integrity of image. This operation will not affect the post-classification task. As shown in Figure 2. Figure 2 (a) is the original image. There are two object, bridge and shoe, in the image. The surface of bridge is rough. But the surface of the shoe is smooth and reflective. Figure 2 (b) is the result of FCN segmentation, blue for the bridge and green for the representative. Figure 2 (c) is the image after filling. We replacing the color of the shoe with the average color of the bridge, removing the color and texture of the shoe.

(a) Original image (b) segmentation result (c) filled image Fig.2 Pretreatment effect

1.2 CNN Crack Image Classification

The CNN is used to classify the image. The used network structure is shown in Figure 3. In the figure, L1, L2, and L3 are convolutional layers, which include convolution, pooling, and activation. L3-1 is convolution layer and L3-2 is pooling and activation. L4 and L5 are fully connected layers. L6 Is a classification layer. L7 is a linear regression layer, connected to L3-1. L8 is a measurement layer.

The convolutional layer is used to extract image features. It performs dot product operations between the input of the image and the convolution kernel. As the number of layers increases, various features from the low level to the high level can be extracted. This paper design the classification task by using the network structure of VGG, and obtains better classification results than the paper [9]. The speed of training is also faster. A plurality of convolution layers alternate with a non-linear activation layer can extracts better features than a single convolution layer. Table 1 gives an example that several feature maps from different convolutional layers of the network used in this paper. The pictures from CONV1 to CONV3 are feature maps[15] obtained after the first to third convolutional layers. It can be seen from Table 1 that due to the single color of the bridge material, the feature map mainly catches the features of the crack image texture.

Choosing appropriate sample is a key factor in improving classification accuracy. A too small image does not accurately reflect the total characteristics of the crack, and an oversized image imposes a large computational burden on the computer. So it is important to select an appropriate image sample size. In this paper, we choose the size of image is 224x224. In the crack detection method proposed in the related paper, the high accuracy rate is accompanied by a high false alarm rate. It means that the proportion of non-crack images classified as crack images is relatively high[6-10]. For example, the false alarm rate of paper[8] is 13.04%. High false alarm rate not only reduces the accuracy of the classification, but also increases the measurement error. In order to solve this problem, the following measures are adopted in this paper: 1. Images with various disturbances are intentionally collected during the collection of images. Let these interference images take part into sample training. 2. Some too small cracks aremanually marked as crack-free labels; 3. Add voting program. Before the classified small images re-spliced into integrated images, the proportion and position of the crack images will be counted. If the number of small crack image is too few or their positional distribution is relatively scattered, the original image is determined to be a crack-free image.

The following conclusions are obtained through many experiments: 1. The crack characteristics are mainly linear and complecated and combined features are not obvious. 2. The increasing number of feature maps significantly accelerates the model training convergence. 3.The sample image of 224 × 224 pixels can ensure that the overall layout of the crack is captured on the basis of accurately identifying the crack.Therefore, the classification task of this paper finally adopts the structure shown in the classification branch of Fig. 3 and we cut the original image into small images of 224 × 224 pixels as input samples.

1.3 Crack Length Measurement Analysis

The classic CNN structure can classify the original image with high accuracy. However, it cannot directly receive the specific crack length value. On the one hand, the crack length is obtained through various measurements and calculations. it is not so possible to intuitively convert the image features extracted by CNN. On the other hand, As each original image has different quality, it is difficult to find a serious of steady processing steps and parameters adapt to all images. In order to solve these problems, this paper applies a linear regression layer to replace the function of tradition many feature maps. We denoted the ideal map as A. A should be the same size as xi prevent from losing information. Obviously, the value of each pixel of A is only related to the value of the pixel corresponding to the input feature map xi, and is independent of the value of the pixel at other positions of xi. Then A can be expressed as:

Before start to train the weight matrix and offset values, It is indespensable to determine whether the fitting image is "good". Firstly, we calculate the the proportion from the unit pixel of shooting position to the actual distance. Secondly, we assume that the ideal image A is obtained and perform the following steps on it:

∧1∨Binarize A and refine it.

∧2∨Remove the area where is smaller than the threshold in the result of (1). The threshold is one of the hyperparameter and its value determined before the training starts. The value varies with the size of image and regardless of the image sample difference.

∧3∨Statistics the number of image pixels in the result of (2).

These three steps of image processing for A are recorded as function F. We measure the length of crack, calculate the length of crack sample and then marked it as y. The least squares feedback is used to learn the weight matrix and the offset. The loss function is expressed as:

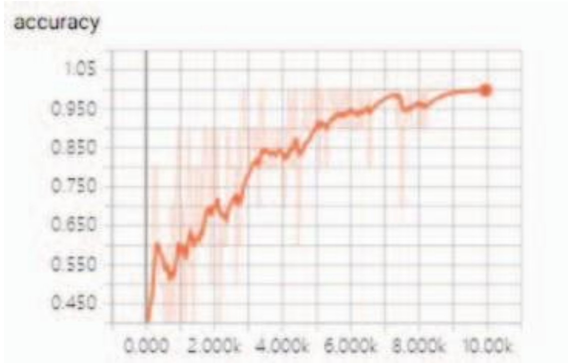
$$f(x) = w_1x_1 + w_2x_2 + \ldots + w_nx_n + b \quad (1)$$

Image is cropped into a smaller image by 224×224 pixels. The image is manually labeled as a crack (positive sample) or a crack-free (negative sample) image. We divided them into training set and verification set[16]. Images of the two sets do not intersect. the training set has a total of 10,000 samples while the verification set is 7771. After that, set the ratio of positive and negative samples in the training set and verification set to 1:1. The training parameters are selected as follows. Iteration time is set to 10000. Learning rate initial is 0.001 and update with the times of iterations. To prevent overfitting, dropout is set to 0.5[17-20]. The results of experiments are shown in Figure 5. Figure 5(a) shows the accuracy of the training. The overall trend of accuracy increases steadily. After 9000 times, our network converges stable; Figure 5(b) shows that the loss function value generally goes a continuous downward trend and finally approaches 0. Figure 5(c) shows the accuracy of the verification set of our network, which overall trend is similar to the training set accuracy. The accuracy of our network for crack classification is above 95%, and the false alarm rate is below 3%.

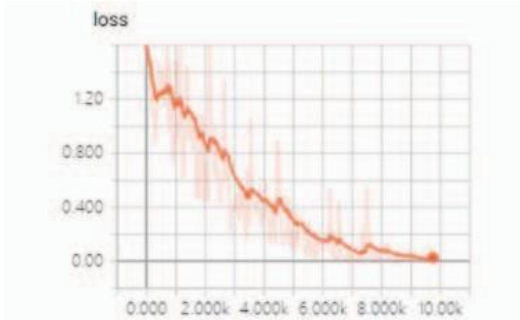
III.RESULTS AND DISCUSSION

A. CNN Network Training and Results Analysis

The CNN network's training method is generally similar to that described in the paper[9]. In a similar vein, the logistic regression is optimised during the training phase by employing a tiny batch gradient with momentum. The training image samples are gathered before we begin training the network. The original image has a resolution of 5472 3078 pixels. An image is cropped to 224224 pixels in size after it has been acquired, and the result is a reduced image. Image labelling is performed manually on each image to determine if it is a crack (positive sample) or a crack-free image (negative sample). We separated them into two groups: the training set and the verification set[16]. The images from the two sets do not cross each other. It is worth noting that the training set contains 10,000 samples, while the verification set contains 771 samples. After that, in both the training set and the verification set, the ratio of positive to negative samples should be set to 1:1. The following are the parameters that were used for training. The number of iterations is set to 10000. The learning rate is initially set to 0.001 and increases as the number of iterations increases. Dropout is adjusted to 0.5[17-20] in order to prevent overfitting. The outcomes of the trials are depicted in Diagram 5. The accuracy of the training is depicted in Figure 5(a). The overall trend in accuracy continues to rise steadily over time. We have reached a stable state after 9000 repetitions; Figure 5(b) illustrates that the loss function value normally follows a continuous downward trend and eventually approaches zero. Figure 5(c) depicts the accuracy of our network's verification set, which displays a general trend that is similar to the accuracy of our network's training set. Our network's accuracy in crack classification is greater than 95%, and the rate of false alarms is less than 3%.



Accuracy of the system



Loss during classification

IV. CONCLUSION

We may conclude that we have created a method that is dependable, inexpensive, and more efficient for native Indian bridges in this manner. This technology will not only be effective for road and pedestrian bridges, but it will also be useful for railroad bridges. This technology will increase the lifespan of various structures by allowing for earlier damage detection, reduce the expense of routine inspections, and, most importantly, improve public safety by eliminating the need for routine inspections. Image processing and machine learning are used in conjunction with bridge crack detection to produce improved results. The input image is pre-processed to remove noise and improve its quality. The image is split in order to identify the Region of Interest. Regardless of whether a crack is evident, classification is carried out.

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