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Implementation of wavelet method and backpropagation neural network on road crack detection based on image processing

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Abstract
Road crack detection is critical to road infrastructure maintenance, requiring sophisticated and accurate approaches. This research uses a combination of Wavelet and Convolutional Neural Network (CNN) methods to improve efficiency and accuracy in detecting cracks in road images. The wavelet method was chosen for its capability to capture information at different scales, enabling improved feature extraction. Meanwhile, CNN was utilized to comprehend the spatial context and tackle image complexity. The research involves several stages, including data collection, pre-processing, decomposition using the Wavelet method, forming of the CNN architecture model, training, testing, and evaluating the result. The tested images involve three main types of cracks: alligator, linear, and images without cracks. The testing results show that the developed model can classify cracks with an F1-score of 0.96, recall of 0.96, and precision of 0.96. In real-time detection of road cracks, the testing obtained an F1-score of 0.84, recall of 0.92, and precision of 0.77. This research contributes to advancing road crack detection technology by leveraging the capabilities of Wavelet and CNN, enhancing the accuracy and efficiency of crack detection in road maintenance.

Keywords:
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Crack;
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INTRODUCTION

Road infrastructure is critical to modern society, facilitating transportation and economic activities [1]. However, the integrity of road surfaces is continuously challenged by factors such as environmental conditions and heavy traffic load, leading to the formation of cracks [2]. Road cracks pose substantial safety risks to motorists and pedestrians and incur significant maintenance costs for governments and road authorities [3]. Detecting and addressing these cracks on time is paramount for ensuring road safety and prolonging the lifespan of road networks [4].

In recent years, computer vision and deep learning advancements have introduced innovative solutions for automated road crack detection and assessment [5]. Convolutional Neural Networks (CNNs), a category of deep learning models, have emerged as a potent tool for image analysis tasks, including detecting road cracks [6]. CNNs can automatically learn and extract intricate features from road images, enabling precise and efficient identification of cracks in various road environments [7].

Adopting Convolutional Neural Network (CNN)-based methods for road crack detection offers several advantages. It reduces the reliance on labor-intensive manual inspections, potentially accelerating the detection process [8]. Furthermore, CNNs can handle large datasets, contributing to the creation of robust models that are capable of generalizing to various road conditions [9]. These capabilities have fueled the development of numerous CNN-based road crack detection algorithms in recent years.

In computer vision, deep learning is the algorithm that has made significant progress. Deep learning is an implementation of an artificial neural network that consists of multiple hidden layers. To improve the detection of road cracks, this study will combine the deep convolutional neural network method with wavelet transformation to enhance the results. The YOLO method was utilized for real-time crack detection. YOLO was chosen for its superior accuracy and speed, as indicated in references [10]. Among its various versions, YOLOv4 stood out as one of the latest iterations, demonstrating a significant 10% enhancement in average precision (AP) on the Microsoft Common Objects in Context (MS COCO) dataset compared to its predecessor, YOLOv3 [11]. Therefore, the YOLOv4 algorithm was utilized in this study for real-time road crack detection.

Numerous studies discuss the detection of road cracks using image processing. For example, based on research conducted by [12]. In a previous study, a deep fully convolutional neural network approach was utilized for the automated detection of concrete cracks, achieving an average precision rate of approximately 90%. The method used in this research effectively detected crack patterns. However, independently measuring the crack size presented challenges, particularly when the test images include various features that resembled disruptive cracks.

In another research project described in reference [13], crack detection was performed using an encoder-decoder architecture incorporating hierarchical feature learning and dilated convolution. The proposed method concludes that the U-HDN method can detect cracks with high performance because it can extract and combine various context sizes and feature map levels from different algorithms. The experimental results revealed that DeepCrack demonstrated resilience towards inaccuracies in crack labeling and effectively handled bright cracks. The weakness of this method is that neural networks have a complex structure with excessive feature maps, which results in high computational costs and low efficiency.

In the research by [14], a technique is proposed that utilizes a deep convolutional neural network for the automated detection of cracks. This technique involves acquiring high-level crack features through learning. In this research, the F1-score exceeded 0.87 across three distinct datasets. The experiments indicated that the DeepCrack approach achieved an average ODS F-measure value surpassing 0.87 on the test datasets, outperforming alternative methods that lacked a decoder network.

In research [15], the evaluation and comparison of machine learning techniques for for crack detection discuss the most recent information. This aims to help other efficiently identify research focus areas. From the results of the conducted research, numerous issues arise with False Positives (FP) and False Negatives (FN) due to inaccurately placed predicted pixels. Post-processing steps that utilize information from the input image range can be explored to address this problem. The boundaries of pavement and other damages that exhibit patterns similar to crack patterns are the primary causes of FP predictions.

From another study [16], the Improved Otsu Threshold method is proposed for road crack detection. The weight of the gray histogram, modified by the probability factor, can enhance the accuracy of target extraction by addressing the issue of prominent use. This solution was developed for processing road images containing various categories of cracks. According to the research results, the method used for crack detection was found to be suboptimal, achieving a precision score of 85% and an F1 score of 88%, both below the 90% threshold.

To enhance the accuracy and reliability of road crack image detection, researchers have adopted a combination of Wavelet and Convolutional Neural Network (CNN) as a significant improvement over previous methods. This study focused on detecting three main types of cracks: alligator cracks, linear cracks, and non-cracks, to over a more comprehensive solution. Wavelet was chosen for its ability to capture high and low-frequency information, enabling better feature extraction for images with varied crack characteristics.

Meanwhile, the integration of CNN enhances the capability to comprehend spatial context and hierarchical relationships among features, enriching the feature representations extracted from the images. Through this combination, the method is expected to overcome the limitations of previous approaches that may be less accurate or efficient in recognizing cracks with different patterns. The results of this research are anticipated to enhance the accuracy and reliability of road crack detection, positively contributing to road infrastructure maintenance technology development.

METHOD

Figure 1 illustrates a flowchart of road crack detection using image processing. Crack road image classification using wavelet-CNN will be compared to real-time road crack detection.

Dataset

The dataset used for this research is representative images such as alligator, linear, and no cracks. This dataset will be used to train and test road crack detection in an image. Figure 2 illustrates an image employed as part of the dataset.

Based on Figure 2, two types of cracks were identified in the research: alligator cracks and linear cracks. Alligator cracks are a type of crack characterized by a wide gap exceeding 3 mm and a pattern resembling the skin of an alligator.

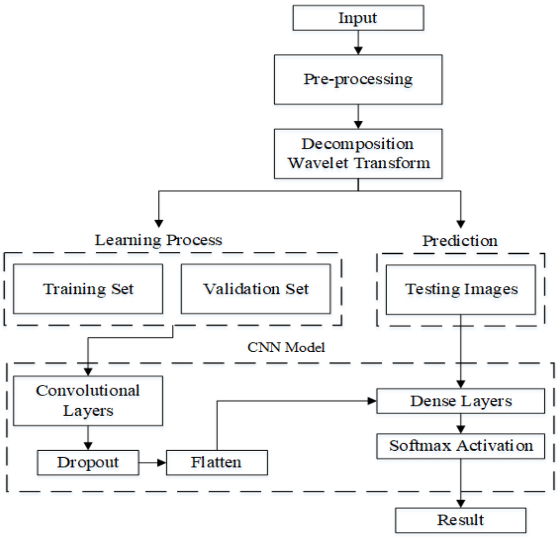

Figure. 1 Proposed method

(a) (b) (c)
Figure 2. (a) Non crack (b) alligator crack (c) linear crack

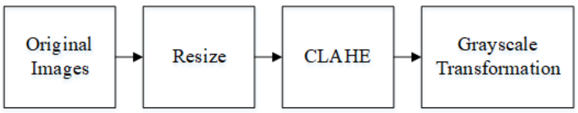

Figure 3. Pre-processing flow

(a) (b)
Figure 4. (a) RGB and (b) Greyscale Image

These cracks are induced by repetitive traffic loads surpassing the capacity of the road surface layer to withstand the loads, accompanied by weathering of the road surface layer. Linear cracks, on the other hand, typically occur in the central area of the pavement, running parallel or in the direction of the road axis. Shrinkage cracks cause linear cracks due to low temperatures in the asphalt pavement surface and the impact of passing vehicle loads.

Preprocessing

In this section, the input image with the original size will be resized to match the image size so that all image data has dimensions of 512x512 pixels. Furthermore, the resized image will be corrected for contrast because the original cracked image dataset is influenced by several factors, such as lighting intensity and camera settings. This image data retrieval produces a variety of image quality. To equalize the quality of the data, contrast settings are made using CLAHE (Contrast Limited Adaptive Histogram Equalization), which aims to get an image with better contrast without compromising image quality. This flow processes a preprocessing image, as shown in Figure 3.

The next process is image grey scaling, starting with the utilization of an RGB image as the initial input, the subsequent step involved extracting the dimensions of the image in order to generate a new one. Furthermore, the RGB image is separated from the component values of red, green, and blue. Then, a new image is created to accommodate the image resulting from the color model change. This process produces a greyscale image as shown in Figure 4.

DWT Decomposition

In the course of discrete wavelet transform decomposition, an image is subject to breakdown into sub-images, known as sub bands, characterized by different frequencies and orientations.

These sub bands are precisely classified into four categories: low-low (LL), low-high (LH), high-low (HL), and high-high (HH) The preprocessed image is used as input for the wavelet transformation to produce four coefficients, namely: coefficient approximation (CA), horizontal detail coefficient (CH), vertical detail coefficient (CV) and diagonal detail coefficient (CD). The results of the transformation will then be used as input for the Convolution Neural Network (CNN) process. This process discrete wavelet transforms decomposition image as shown in Figure 5.

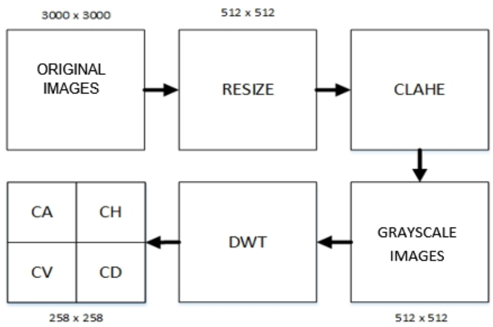

Figure 5. Descartes wavelet transform decomposition flow

Realtime Detection using YOLO

Initially, YOLO was a pre-trained object detection model that had been specifically trained to recognize common objects in its repertoire, including items like tables, chairs, cars, phones, and more. In this paper, YOLOV4 is used to detect road cracks in real time. By changing the hyperparameters, it can be used to train and test using a dataset of road crack images, namely alligator cracks and line cracks. Figure 6 illustrates a flowchart of YOLO method.

Data preprocessing consists of converting video into an image, which will then be labeled according to its class name, which aims to store image information.

Labeling involves associating each object within an image with a class name and providing a bounding box. The data annotation process commences by outlining a bounding box around each object within the image, in this instance, characters. Subsequently, the details of the bounding box are saved in a file, including the values of c, (x, y), (w, h), which respectively represent the object class, the coordinates of the bounding box's center point, and the dimensions of the bounding box.

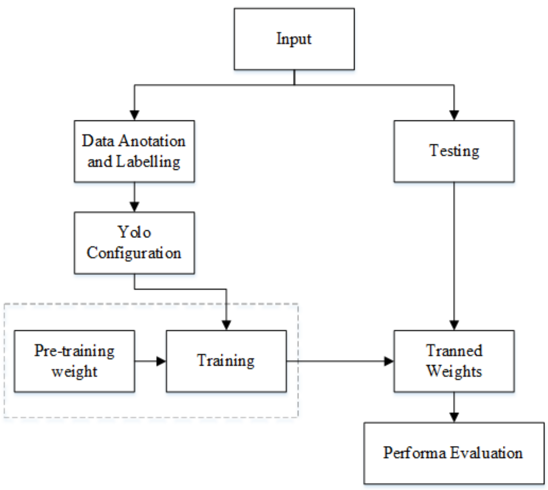

Figure 6. Proposed YOLO method

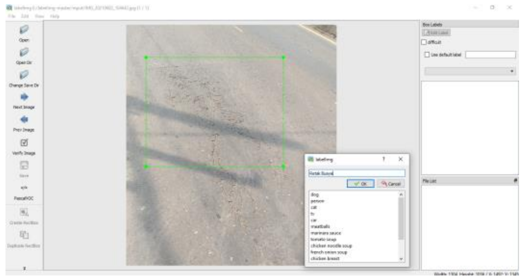

Figure 7. Data labeling

The description of the created bounding box is then compared to the original image's dimensions to ensure that the bounding box information remains proportional in varying image sizes. The annotation encompasses two object classes, namely crocodile cracks and line cracks. An illustration of data annotation is shown in Figure 7.

We are using the darknet framework from GitHub which provides training section code and runs the trained model. However, we need to practice the model on the crack road dataset and generate a trained model. We trained on the original YOLOv4 architecture and a customized version of the YOLOv4 architecture using the road crack dataset. The input image size in this experiment is 320x320 and the learning speed is 0.001. We opted for a 320-image patch size to streamline and confine the computations.

Weight storage was performed at intervals of every 1000 epochs to enable the calculation of mAP results for verification purposes. Initially, the YOLO model was a pre-trained object detector designed to recognise common objects like tables, chairs, cars, phones, and more. In this study, YOLOV4 was employed for real-time road crack detection. The adjustment of hyperparameters allowed us to train and evaluate its performance with a dataset of road crack images, specifically identifying crocodile and line cracks.

Proposed Architecture

This section of the study describes the architecture of the proposed model used for road crack detection. The model is a combination of image texture analysis and machine learning. Input image is used to wavelet method from dataset. Based on the extracted feature and classification used CNN The model architecture is illustrated in Figure 8.

In our proposed CNN architecture, We incorporated three convolutional layers, each followed by max-pooling and an additional layer to perform feature extraction. Our CNN model aimed to achieve high accuracy while maintaining efficient computational speed, and enhancements were introduced through the utilization of max-pooling, dropout layers, flattening, and dense layers. The activation function used is the rule. The rule activation function has better achievement in creating multi-layer performance and convolutional networks. In the training process, the epoch iteration will be set 300 times and use max poll will be used to take the highest value from the convolution matrix to reduce the time during the computation process.

Prediction Scheme

This flow process produces a prediction image as shown in Figure 9.

The evaluation of a classification model's effectiveness hinges on certain performance measurement metrics, specifically accuracy, recall, precision, and F1 score. These metrics are typically computed using a matrix commonly known as the confusion matrix. Within the confusion matrix, several values are taken into consideration, including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP and TN represent the probabilities of correctly identifying positive and negative events, respectively [17][18].

Accuracy is an evaluation metric that measures the extent to which a classification model is able to make correct predictions across the entire dataset. In the context of classification, accuracy assesses the percentage of correct predictions out of the total number of predictions. he formula to calculate accuracy is:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

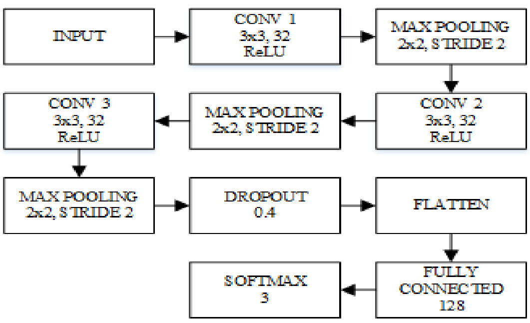

Figure 8. CNN architecture

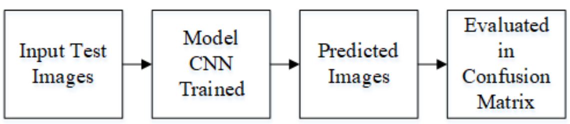

Figure 9. Flow prediction images

This metric provides an overall overview of the model's performance, encompassing both positive and negative class predictions. While accuracy can offer a general indication of how well the model functions, it's important to note that if the class distribution is imbalanced, accuracy may not accurately reflect the model's performance, especially regarding minority classes.

Precision is an evaluation metric that assesses the accuracy of positive predictions made by a classification model. Specifically, precision measures the ratio of true positives to the sum of true positives and false positives. In mathematical terms, precision is calculated using the following formula:

$$Precision = \frac{TP}{FP + TP} \quad (2)$$

This metric is particularly relevant in scenarios where the focus is on minimizing false positives, as it provides insights into the model's ability to make accurate positive predictions. A high precision score indicates that the model has a low tendency to misclassify negative instances as positive.

Recall, also known as sensitivity or true positive rate, is an evaluation metric that measures the ability of a classification model to identify all relevant instances of a positive class correctly. In other words, recall quantifies the proportion of true positives to the sum of true positives and false negatives. The formula to calculate recall is as follows:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

This metric is particularly valuable in scenarios where the emphasis is on minimizing false negatives, as it provides insights into the model's capability to capture and identify all positive class instances. A high recall score indicates that the model has a low tendency to miss positive instances. Recall is crucial in applications where failing to identify positive instances can have significant consequences, such as in medical diagnoses or security systems.

F1 score is a metric that combines both precision and recall into a single measure, providing a balanced assessment of a classification model's performance. It is particularly useful when there is a need to balance minimizing false positives and false negatives. The F1 score is calculated as the harmonic mean of precision and recall using the formula:

$$F1score = 2 \times \frac{(Precision \times Recall)}{Precision + Recall} \quad (4)$$

The F1 score ranges from 0 to 1, where a higher score indicates a better balance between precision and recall. This metric is valuable in scenarios where an equal consideration of false positives and false negatives is important, and it helps evaluate the model's overall effectiveness in handling both positive and negative instances. Researchers often utilize the F1 score when assessing classification models in situations where there is an imbalance in class distribution or when the cost of false positives and false negatives needs to be equally addressed.

RESULTS AND DISCUSSION

Wavelet-CNN

From the results of Figure 10, it can be seen that the validation data cannot be classified correctly according to the label. In the data labeled crocodile crack, 55 data are classified correctly; 1 data is classified as line crack, and 1 data is classified as not cracked. In the data labeled line crack, 63 data classified correctly, 1 classified as crocodile crack class, and 4 classified as non-cracked class. In the data labeled as uncracked class, 51 data are classified correctly; 0 data is classified in the crocodile crack class, and 0 data is classified in the line crack class.

Model evaluation was conducted to determine the model's ability to classify images. This evaluation is obtained from the classification results of the testing data. The performance of the highway crack detection system was assessed by computing the precision, recall, and F1-score values. Table 1 shown the results of testing the performance of the crack detection system.

Based on Table 1, the proposed methods, CNN and the wavelet model, have proven to be effective in successfully detecting road cracks, exhibiting strong performance. For the classification of alligator cracks, precision score of 0.98, recall score of 0.96, and F1 score of 0.97 were achieved.

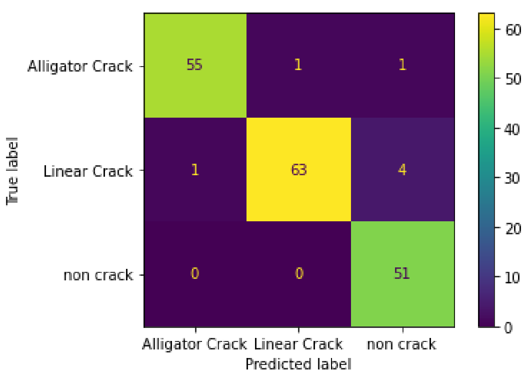

Figure 10. Confusion matrix

Table 1. Performance metrics of proposed Wavelet CNN for crack road detection

	Precision	Recall	F1-score	Support
Alligator	0.98	0.96	0.97	57
Linear	0.98	0.93	0.95	68
None	0.91	1.00	0.95	51
Macro average	0.96	0.96	0.96	176
Weighted average	0.96	0.96	0.96	176

In the classification of linear cracks, precision score of 0.98, recall score of 0.93, and F1 score of 0.95 were obtained. In the classification of non-cracked images, the precision score of 0.91, recall score of 1.00, and F1 score of 0.95 were obtained. Furthermore, the average scores from the utilized model are as follows: accuracy score of 0.96, precision score of 0.96, recall score of 0.96, and F1 score of 0.96. Table 2 shown a comparison between our proposed approach and alternative others methods to evaluate the performance of the crack detection system for testing the performance of the crack detection system

Based on Table 2, which compares the results of this research, we compared the findings from our study, which had already been conducted, with those of other studies focusing on road crack detection using image processing. Our method showed superior performance compared to other methods, with higher accuracy, precision, recall, and F1-score results. Meanwhile, the UNET CNN method exhibited the lowest performance in terms of accuracy, precision, recall, and F1-score compared to the other benchmark methods. This study depicted significant progress in addressing the researched problem and highlighted the potential for the use of newer, more effective methods in this context. These results underscore the importance of ongoing research and the development of methods that can enhance solution quality in the field of image processing.

Realtime

Experimental environment of this paper uses Google collaborative to conduct training and testing. Google Collab features a 12GB NVIDIA Tesla K80 GPU which is compatible with DARKNET. DARKNET is written in C and CUDA. The NVIDIA CUDA deep neural network library (cuDNN) is used to make it all work. In the test, two types of road cracks were classified, namely: crocodile cracks and line cracks. Table 3 shown the results of the system testing process using test data.

Table 2. Comparison Between Our Proposed Method and Other Methods

Author	Methods	Acc. (%)	Prec. (%)	Recall (%)	F1 (%)
[19]	UNET CNN	-	74.26	72.85	73.27
[20]	LBP-PCA-SMV	85.29	-	-	-
[21]	CNN	89.67	86.90	81.80	84.20
[22]	Otsu's Thresholding	95.90	93.39	98.48	94.62
[23]	SMV	96.25	93.02	92.50	
[24]	YOLOV5	-	95.30	83.40	88.90
[25]	Encoder-Decoder	-	84.13	81.20	82.64
[26]	High-resolution network	-	91.54	92.38	92.38
[27]	KNN	90.00	-	-	-
	Our method	96.00	96.30	95.80	96.00

Table 3. Performance metrics of proposed Yolov4 for crack road detection

IOU	Pre.	recall	F1-score	Average IOU	mAP
map@50	0.77	0.92	0.84	0.51	0.88

Figure. 11. Sample detections

Based on Table 3, YOLO succeeded in detecting road cracks and the evaluation results of network performance reached mAP 88,285, precision 0.772, recall 0.918, and F1-score 0.838. Some of the sample detections are shown in Figure 11. The network outputs a name and accuracy for each detected crack.

Figure 11 shows the detection results of our methods on road surfaces experiencing alligator cracks, linear cracks, and non-cracked conditions. The results demonstrate that our method can detect real-time road crack, with performance scores as shown in Table 3.

CONCLUSION

In this paper, we propose the combination of wavelet and CNN method for road crack detection with an image as input and use the Yolov5 method to detect road cracks in real-time. In the experiment using the wavelet-CNN method, the F1-score performance test results were 0.96 and in the Yolo method, the F1-score performance test results were 0.84 and the mAP (mean average precision) 0.88.

From this paper, it can be concluded that wavelet-CNN is able to detect road crack images well. Although there are still misclassifications between crack types, such as crocodile cracking which is predicted to be line crack, perhaps this is due to the insufficient number of road crack type datasets for training and the poor image quality due to noise in the image dataset. Likewise, the yolo method is also able to detect road crack images well. The test results show that the detection model can quickly detect road cracks in real-time. However, the model has a certain degree of missed detection. As a future work, the types of road damage will be added and the dataset will be reproduced to get a better model.

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