

Road Crack Detection using Yolo-V5 and Adaptive Thresholding

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Abstract - Road crack detection is a critical aspect of infrastructure maintenance, ensuring the safety and durability of roadways. This study presents an innovative approach leveraging image processing techniques, YOLO-V5 model, and adaptive thresholding for efficient and accurate road crack detection. The utilization of adaptive thresholding enables the system to handle complex lighting variations and diverse road textures, enhancing the precision of crack identification. Integrating the YOLO-V5 model further facilitates real-time detection and precise localization of road crack regions, contributing to effective and timely maintenance strategies. The research findings underscore the robustness and efficacy of the proposed methodology, emphasizing its potential for enhancing road safety and durability.

Keywords – Road Crack, Image Processing, Yolo-V5, Adaptive Threshold

1. INTRODUCTION

Image processing is a branch of computer science that deals with the analysis, manipulation, and understanding of images and visual data [1], [2]. It involves various techniques and algorithms to enhance images, perform feature extraction, and recognize patterns within images. Image processing encompasses a series of steps, ranging from pre-processing to advanced image analysis, including object detection, image segmentation, and image reconstruction. Meanwhile, image detection is an essential subfield of image processing aimed at identifying the presence or location of specific objects or features within an image [3]. Image detection methods include various techniques such as edge detection, feature detection, and statistical modeling, used to identify objects, cracks, or other important elements within the image [4], [5]. With the development of technology and artificial intelligence, the applications of image processing and image detection have expanded to fields such as computer vision, pattern recognition, and other image processing [6].

Road crack detection involves the utilization of image processing techniques to identify and map cracks on road surfaces [7], [8]. In this context, edge detection, image segmentation, and feature analysis are crucial techniques for recognizing and distinguishing cracks from other elements in road images [9]. Image detection methods such as the Sobel filter or threshold-based segmentation algorithms can be employed to highlight suspicious areas as cracks [10], [11]. Moreover, the use of deep learning-based image processing has gained popularity in enhancing detection accuracy.

In this research, a combined approach of YOLO-V5 model and adaptive thresholding method is employed for detecting road crack areas. YOLO-V5, a renowned deep learning-based object detection model known for its high speed and accuracy, is utilized to identify the general

locations of cracks in road images. Subsequently, the adaptive thresholding method is used to achieve more precise detections by adjusting the threshold adaptively based on the local pixel intensity characteristics. This combined approach enables accurate and efficient crack detection, capable of handling variations in lighting conditions and complex road textures. The research findings demonstrate the reliability and effectiveness of this approach in identifying road crack areas with high accuracy and rapid response time.

2. RESEARCH METHODOD

Based on Proposed Method, the methodology follows a sequential approach starting with the input image acquisition, followed by pre-processing steps to enhance the image quality and reduce noise. The pre-processing stage involves techniques such as image resizing, noise reduction, and contrast enhancement. Subsequently, the adaptive thresholding method is applied to the pre-processed image to identify potential crack areas based on the local intensity variations. The detected regions from the adaptive thresholding process are then further analyzed using the YOLO-V5 model, a robust deep learning-based object detection framework, to accurately locate and classify road crack regions. The proposed methodology aims to integrate the strengths of both adaptive thresholding and YOLO-V5 to achieve a comprehensive and precise road crack detection system capable of handling diverse lighting conditions and complex road textures. Figure 1. Represents the flow of research methodology.

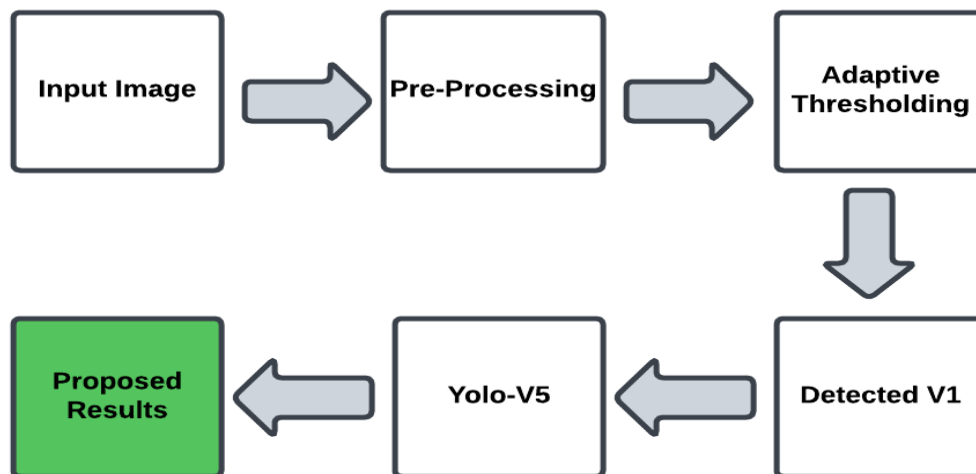


Figure 1. Research Methodology

2.1. Datasets

Dataset used in this study was obtained from a publicly available source, comprising a total of approximately 9000 images, each with a resolution of 512 x 512 pixels and three color channels. The dataset was sourced from Kaggle, a well-known platform for hosting various datasets, and it encompassed diverse images capturing different road conditions and environments [12]. The dataset was manually curated and labeled by domain experts to ensure the accuracy and relevance of the data for road crack detection analysis. Figure 2. Represents Sample of image Datasets.

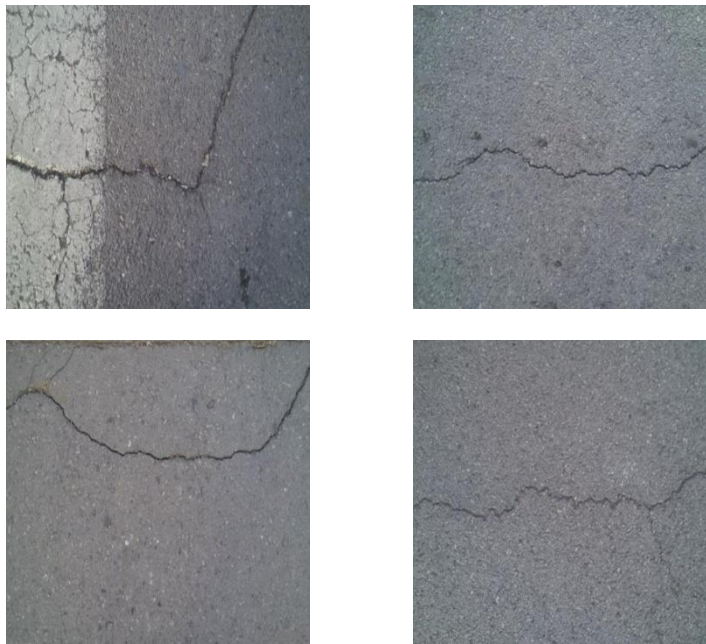


Figure 2. Sample Image Datasets

2.2. Pre-Processing

In the pre-processing stage, a series of steps are conducted to prepare the images prior to further analysis. Contrast enhancement and image refinement are employed to improve the clarity and quality of the images, as well as to enhance the system's capability to detect crucial details [13], [14]. Adjusting the contrast aims to increase the distinction between neighboring pixels, while overall image enhancement aims to improve the brightness and sharpness of the image. These measures not only facilitate more accurate road crack detection but also ensure that the processed images meet the required quality standards for subsequent analysis [15]. Thus, pre-processing becomes a critical step in preparing the dataset before implementing further road crack detection techniques. Figure 3. Represents the pre-processing phase.



Figure 3. Image Pre-Processing

2.3. Adaptive Threshold Processing

Adaptive thresholding represents a widely employed technique in road crack detection, specifically designed to handle complex variations in lighting intensity and significant texture differences on road surfaces [16], [17]. This method enables the creation of adaptively adjusted

threshold values for each pixel based on its local environment, facilitating more precise detection of cracks with varying intensities. By implementing adaptive thresholding, suspicious image areas can be efficiently identified as cracks, leading to more accurate and detailed detection of road damages [11]. This approach significantly improves the performance of road crack detection under varying lighting conditions and complex environmental settings, thereby enabling more effective and timely road maintenance. Figure 4. Represents Adaptive Threshold Processing per Alpha.

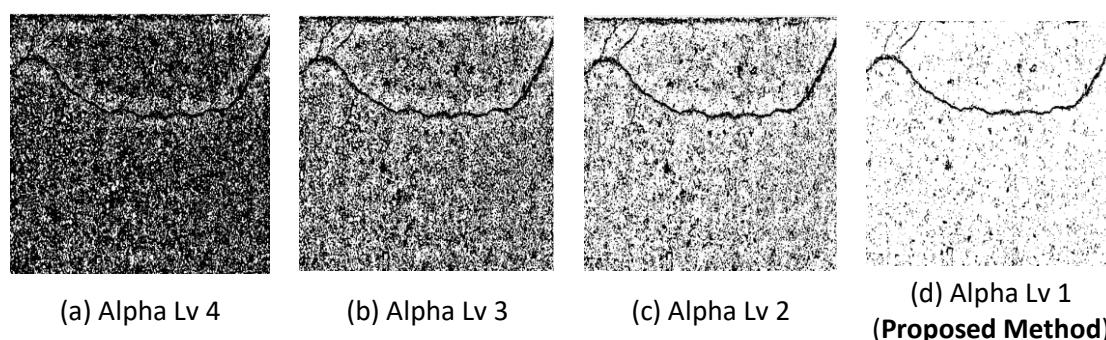


Figure 4. Represents Adaptive Threshold Processing per Alpha

2.4. Yolo-V5

The YOLO-V5 model serves as a robust deep learning-based framework widely employed for the identification and classification of road cracks with enhanced precision and efficiency [18]–[20]. Leveraging its advanced architecture, YOLO-V5 is capable of real-time object detection, enabling the accurate localization and recognition of road crack regions within complex road images. Based on Yolo-V5 Algorithm can be seen below.

START

Input: Preprocessed image

Load the pre-trained YOLO-V5 model

Convolutional Layer:

Convolutional layer with *64 filters and a 3x3 kernel size*

Batch normalization

Leaky ReLU activation function with *alpha = 0.1 to 0.4*

Max pooling with a *2x2 pool size*

Residual Block 1:

Residual connection

Convolutional layer with *128 filters and a 3x3 kernel size*

Batch normalization

Leaky ReLU activation function with *alpha = 0.1 to 0.4*

Convolutional layer with *64 filters and a 1x1 kernel size*

Batch normalization

Leaky ReLU activation function with *alpha = 0.1 to 0.4*

Output: Predicted classes and bounding boxes

END

3. RESULTS AND DISCUSSION

Based on the methodology above, the results and discussion section provides a comprehensive analysis of the outcomes obtained from the implementation of the proposed

approach for road crack detection. This section aims to present and interpret the findings derived from the adaptive thresholding and YOLO-V5 techniques, elucidating their combined efficacy in accurately identifying and localizing road crack regions within diverse environmental conditions and complex road surfaces. The first step involves the pre-processing and image segmentation based on adaptive threshold, as illustrated in Figure 5.

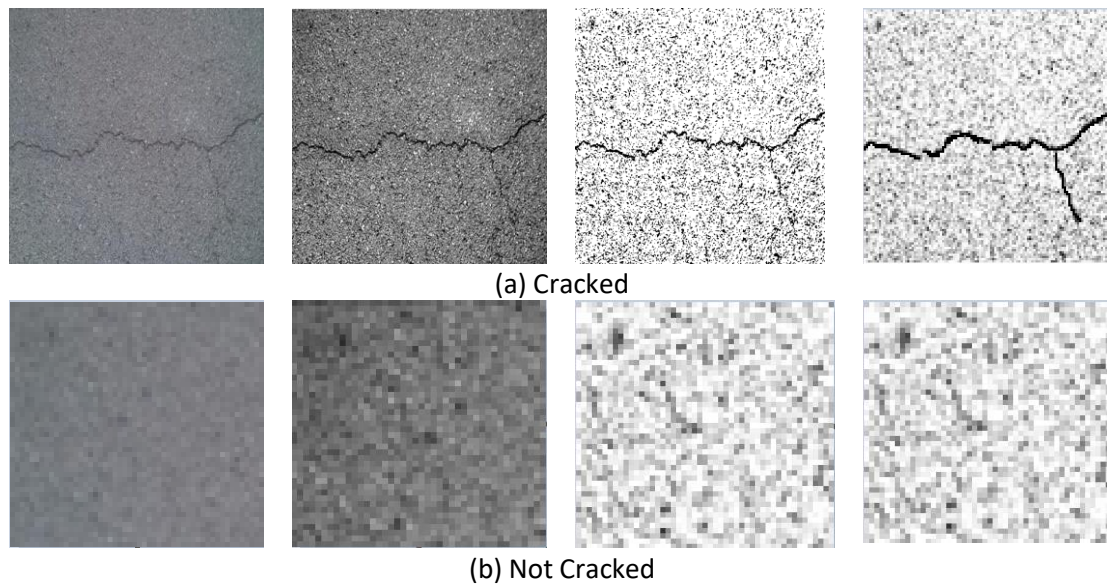


Figure 5. Image Pre-Processing and Image Segmentation

Subsequently, the implementation of the YOLO algorithm, as depicted in Figure 6, is executed after this stage. The YOLO algorithm aids in the precise identification and classification of road crack regions, enhancing the system's capability to detect and analyze intricate crack patterns within the road images.

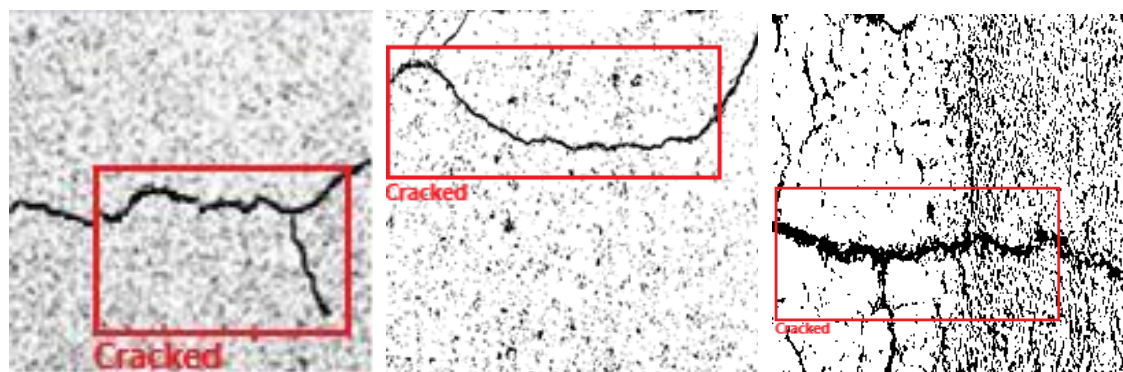


Figure 6. Implemented Yolo-V5

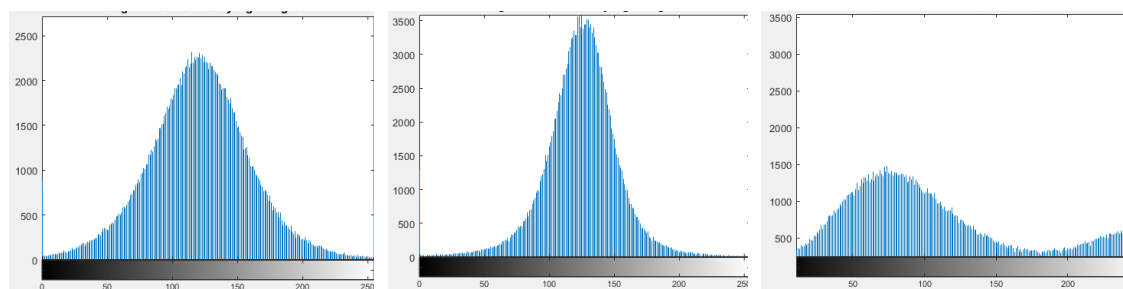


Figure 7. Histogram From Implemented Yolo-V5

4. CONCLUSION

The study successfully demonstrates the effectiveness of the combined approach employing adaptive thresholding and the YOLO-V5 model in the accurate detection and localization of road crack areas. The utilization of adaptive thresholding allows for improved detection under varying lighting conditions and complex textures, enhancing the precision of identifying potential road damages. Moreover, the integration of the YOLO-V5 model significantly enhances the efficiency of the detection process, providing real-time and reliable identification of road crack regions.

The developed system showcases promising capabilities for addressing critical challenges in road maintenance, contributing to the overall improvement of infrastructure safety and durability. Further research efforts focusing on the integration of additional deep learning techniques and the refinement of the detection algorithms are recommended to enhance the system's performance and expand its applicability in diverse real-world scenarios.

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