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Concrete Crack Detection, Orientation and Measurement Using a Wall Climbing Robot

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Abstract: Concrete structure damage and severity are determined by examining the width of cracks in various forms. This categorisation of cracks is based on their specific types, which is crucial for engineers and professionals. It allows them to efficiently prioritise maintenance and repair efforts, extending the lifespan of concrete structures. Thus, the classification of cracks is based on the type of cracks needed. This study combines a wall-climbing robot equipped with imaging capabilities to automate the detection and classification of cracks in concrete surfaces. We used machine learning to classify the crack orientation and OTSU to segment the crack shapes. Based on this study, four experiments were carried out using machine learning methods to classify types of cracks, which are SVM, Random Forest, KNN, and Decision Tree. These experiments were categorised using multiclass classification with types of the orientation of crack such as Not crack, Crocodile, Transverse, and Longitudinal. The classification one-class results show that the Decision Tree achieved 86.50%, SVM 99.50%, Random Forest 97%, and KNN 40%. In multiclass classification, Decision Tree achieved 64%, Random Forest 80%, and KNN 37%. The higher accuracy from SVM is achieved at 87%.

Keywords: Artificial intelligence; Crack detection; Image processing; Machine learning; Wall climbing robot.

1. INTRODUCTION

Structural Health Monitoring (SHM) is used in civil engineering to monitor the health of structures such as buildings and bridges [1]. SHM is a process that involves tracking, identifying, and measuring features of interest from structure responses to detect damage and improve safety. Several practical tools for detecting damage in structures include visual inspection and non-destructive tests such as ultrasonic, radiography, and acoustic emission. Traditional crack detection still uses professionals to inspect the concrete structure manually as shown in Figure 1. This inspection method is not only labor-consuming but also time-wasting [2]. Therefore, localised measurements are also necessary to accurately pinpoint the damage [1]. The crack starts from small propagation and then becomes large. Thus, crack is a dangerous disease, such as cancer, which must be treated early and will become destructive later [3]. Early crack detection is important because their propagation growth causes fatal damage and building structure collapse [4].

Figure 1. The current method for Structural Health Monitoring.

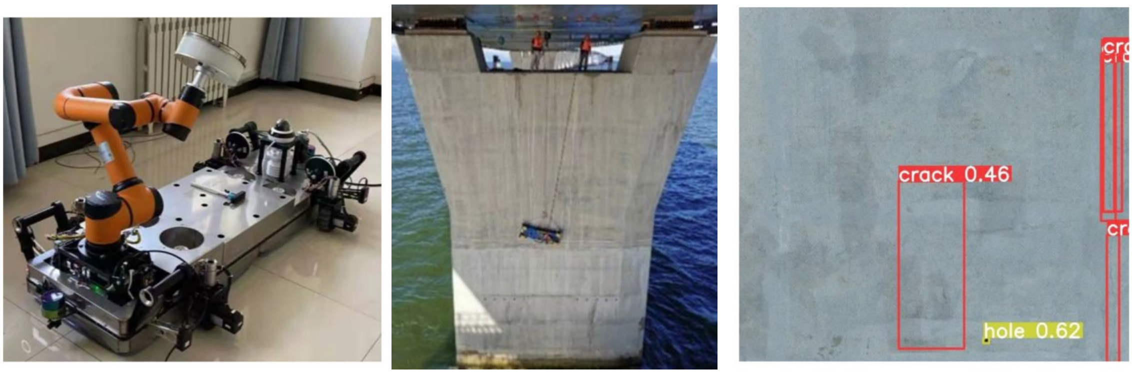


Figure 2. Heavy load wall climbing robot [6].

The Wall Climbing Robot (WCR) has gained interest over the years as a promising approach for remote inspection and maintenance of high-risk areas. Thus, WCRs have emerged as an essential surveillance technology for accomplishing tasks in considerably challenging environments like extensive structures of buildings and huge bridges, which offer the advantage of reaching certain points that are not advisable for human beings, such as construction buildings on higher grounds [5], [6]. Figure 2 shows one application of the WCR. Previous work [7] presents a propeller-type wall-climbing robot applied to the visual and hammering inspection of the concrete surface, which is beneficial and practical for crack inspection of concrete walls. This robot is intended for inspecting the concrete surface and thus can be used for the task of crack detection in concrete structures using a robot.

Crack detection is an important part of inspecting and evaluating concrete structures. It helps to determine the structure's safety, durability, and applicability [8]. In recent years, researchers have used a variety of machine learning to detect concrete cracks. This approach is to analyse images of concrete surfaces and identify areas that contain cracks. Our previous work using deep learning faced computation time and efficiency issues, particularly in robotic implementation [9], [10]. Deep learning takes a lot of computation time [11]. Thus, the Raspberry Pi struggled to handle detection, segmentation, and measurement simultaneously due to the high computational cost, exceeding the capabilities of a mini PC. Therefore, we switched to a machine-learning model such as Decision Tree, Support Vector Machine (SVM), Random Forest, and k-nearest neighbors (KNN). The proposed crack detection consists of four phases: Pre-processing, feature extraction, classification, and segmentation and measurement.

Crack detection is a challenging task due to the presence of noise and other image artefacts. In order to improve the accuracy of crack detection, it is often necessary to apply image processing techniques to the images. One common approach is to use filters to smooth the images and remove noise. This research uses a median filter with gamma correction as a filtering method. This filter aims to reduce pixel noise and smooth images while preserving contour. The median filter is a non-linear method [11], replacing each pixel intensity value with the median intensity value of a set of surrounding pixels while keeping the edges. Gamma correction makes the dark areas of the image darker and the bright areas of the image brighter. A study by [12] found that gamma correction can enhance the small details, texture, and contrast, making it suitable for concrete cracks.

Feature extraction involves identifying and extracting important and distinctive attributes from a dataset. These attributes, referred to as features, are commonly utilised in classification, clustering, and regression tasks. Image processing aims to identify and recognise object shapes in digital images [12]. It can extract specific features to detect crack shapes. These features encapsulate valuable information about the crack, such as edge details, texture characteristics, pixel intensities, and the contrast between the foreground (crack) and background [13].

This study used a wall climbing robot equipped with an Electric Ducted Fan (EDF) to explore the concrete surface. The robot is equipped with a camera to detect and measure the size and orientation of cracks. The robot can identify and measure various cracks by applying machine learning algorithms and computer vision methodologies. In addition to wall-climbing capabilities, this study also incorporates several pre-processing methods, such as image filtering and gamma correction, to preserve edges and remove noise. Feature extraction was performed using the inverted Otsu method and image dilation. Next, the crack features were classified using several machine learning methods, followed by segmentation of the crack shape using Otsu and measurement by Euclidean distance.

2. MATERIALS AND METHOD

The proposed crack detection consists of four phases: Pre-processing, feature extraction, classification, and segmentation and measurement. In the pre-processing stage, the image undergoes several transformations, starting with grayscale transformation, which converts the image into grayscale. this is followed by image filtering using a median filter to reduce noise while preserving important edges, ensuring the cracks remain clear from noise. additionally, illumination correction with gamma correction is applied to adjust for uneven lighting, enhancing the contrast of the cracks. thus, during the classification phase, machine learning techniques such as Decision Trees, SVM, Random Forest, and KNN are used, and their results are evaluated using a confusion matrix to select the model with the best accuracy. Last, the segmentation and measurement stage examines the crack detection through Otsu thresholding and moves forward to characterise the type and orientation of cracks. The proposed framework can be shown in Figure 3.

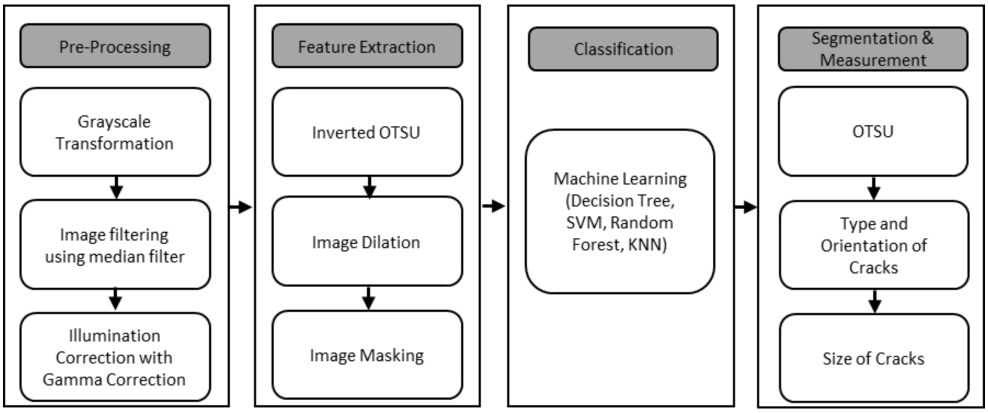
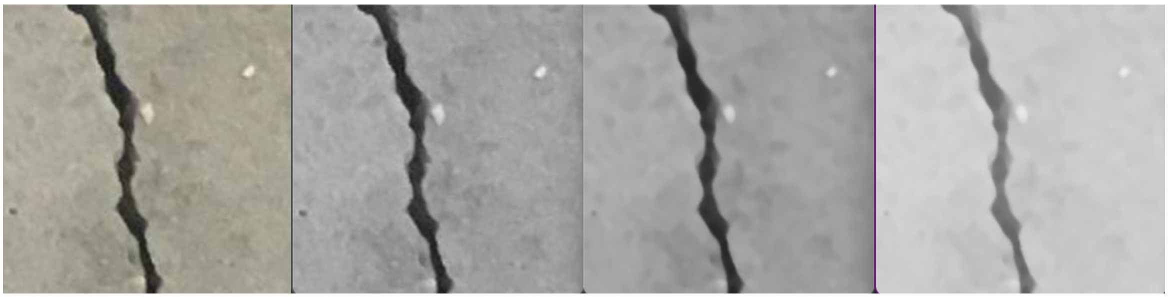


Figure 3. Proposed framework.



Input image Grayscale Median filter Gamma correction

Figure 4. Pre-processing process.

2.1 Pre-Processing

This pre-processing method thoroughly evaluates each stage to address the particular issues of finding cracks in real-world images. The pre-processing and feature extraction processes consider noise, uneven lighting, and complex backgrounds. First, grayscale transformation is used to reduce colour information for focusing on intensity values, simplifying the problem while maintaining significant visual variances [14]. Noise reduction is needed in real-world applications because surfaces being examined for cracks contain various forms of visual noise. It may originate from differences in the texture of the surface, dirt, shadows, or defects not associated with the cracks themselves. Thus, in the second step, a median filter is used to preserve the edges of cracks, which is crucial in this application. This study uses a 5x5 kernel for the median filter, which is a reasonable choice for balancing noise reduction and edge preservation. Kernel 5x5 has more contrast value than 3x3, 7x7, 9x9 or 11x11, and the same is true for experiments by [15]. However, in real-world scenarios, cracks are also infrequently obtained under optimal lighting conditions, and cracks may be small or disguised due to shadows or glare. Thus, gamma correction is a particularly insightful addition to this process, for it helps to correct uneven lighting and enhance the visibility of cracks, which separates cracks and noise. Gamma correction enhances the differentiation between the crack and its background, allowing for more effective segmentation through thresholding techniques, such as Otsu's thresholding, used in this study. The pre-processing stages are shown in Figure 4.

2.2 Feature Extraction

Feature recognition can extract geometry information [16]. There are two categories of image features: low-level and high-level features [17]. Low-level image features, including shape, colour, and texture, are obtained through image processing, whereas high-level features correspond to the words or concepts conveyed by the image. The low-level feature is an easy way to extract from the crack. The crack edges provide insights into its shape and outline, while texture characteristics offer information about its surface properties that can be used as features of the cracks. Additionally, pixel intensities and the contrast between the foreground and background contribute to understanding the crack visibility and distinguishability from its surroundings. In the study, inverted Otsu thresholding is used to separate the image's foreground (crack regions) and background pixels. Otsu's thresholding automatically determines an optimal threshold based on the histogram of pixel intensities. By inverting the result of the thresholding operation, the cracks are highlighted as foreground regions against a darker background. The result of the inverted Otsu thresholding operation provides a binary image with pixel values of 0 (background) and 1 (foreground). These binary values can be considered as features that represent the presence or absence of cracks in the image. The cracks are represented by the value 1, which serves as an essential characteristic or feature for subsequent analysis. Image dilation is applied to enhance the cracks further and make them more distinguishable. Dilation expands the boundaries of the foreground regions (cracks), making them thicker and more prominent. This study scales 1 pixel from the boundaries to give an area of Otsu when segmenting the pixel using dilation, which is useful to calibrate the measurement by Otsu segmentation. This accentuation of the crack structure aids in the extraction of more distinctive features. Figure 5 shows the feature of extraction process.

2.3 Classification

Detecting and classifying cracks using quantitative analysis plays an important role in determining the severity of cracks [18]. Automating the process makes crack evaluation faster. It makes crack assessment more accurate and saves a lot of time and effort compared to manual inspections. The classification process is designed to sort cracks according to their types and orientations. The development of a machine learning model necessitates the use of both training and testing data. This specific model employs a dataset that is divided into an 80:20 ratio. Here, 80% of the dataset is allocated for training purposes, while the remaining 20% is set aside for validation. The training set contains 80% of the data, allowing the model to learn from diverse examples. A 60:40 or 70:30 split would reduce the training data available for the model, potentially leading to underfitting, where the model fails to learn adequately from the training set due to insufficient data. Thus, this study used three machine learning classifications to compare the best machine learning to classify the crack such as SVM, Random Forest, KNN, and Decision Tree. The classification results are shown in the images in Figure 6.

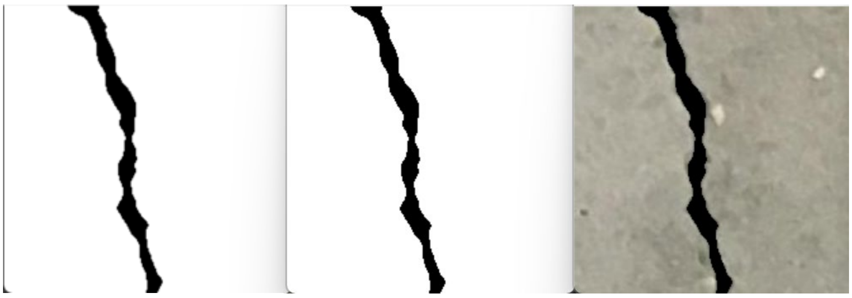
2.4 Segmentation and Measurement

The Otsu thresholding method is a popular technique for image thresholding, which is the process of converting an image from a grayscale to a binary image. In a binary image, each pixel is either black or white. Otsu can be used in the feature extraction of the crack [19] and once in the crack segmentation [20]. The Otsu thresholding method works by finding the threshold value that maximises the variance between the foreground and background pixels in the image. The foreground pixels are the pixels that are part of the object that is being segmented, and the background pixels are the pixels that are not part of the object.

Measuring the size of cracks involves iterating through the contours, assessing the size of each crack, and drawing bounding boxes based on these contours. This method allows for a detailed analysis of the cracks. After the bounding box is detected, Euclidian distance is applied to measure the length and width of the crack. The Euclidean distance can be used to measure the crack length [21]. The distance between two points is measured as the straight-line distance between the points and converted to a millimeter unit. The measurement process can be shown in Figure 8.

2.5 Dataset

The study uses a conventional dataset called "Concrete Crack Images for Classification" from the Mendeley Dataset, which contains 40,000 images of 227 × 227 pixels. This dataset contains 20,000 images of crack and 20,000 images of non-cracked. It is easy to understand the class labels of images, cracked and non-cracked. The dataset includes labelling on cracked and non-cracked status. In previous research by [22], the researcher used multiclass cracks divided into three classes: Crocodile, Longitudinal, and Transverse. They tested 250 images per class (200 images for training and 50 for testing) for 600 training data and 150 for validation, with total 750 images. The same amount of experiment data was used in this study, but no overall data was used. This study randomly selected 250 images in each class, including non-crack images with a total 1000 images. Thus, this research used 800 training images and 200 testing images for validation with four classes (Crocodile, Longitudinal, Transverse, and non-cracks).

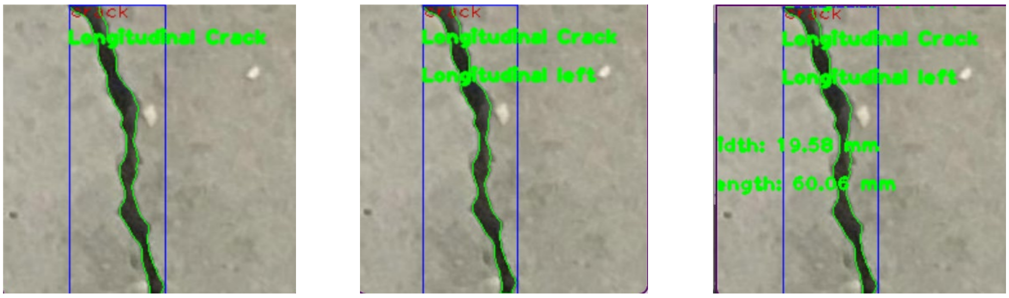


Inverted OTSU Image dilation Image masking

Figure 5. The feature extraction process.

Figure 6. Machine learning classification.

Figure 7. OTSU segmentation.



Measure the size of the crack using Euclidean distance | Calculate the orientation of crack based on bounding box direction | Create a bounding box and show predict types of crack

Figure 8. Crack measurement process.

2.6 Evaluation

A confusion matrix is a tool used in classification problems to evaluate the performance of a classifier. It can be used to evaluate the performance of a machine-learning model [17]. It provides a quantitative measure of the model's ability to accurately identify and classify different types of concrete cracks in images. The model accuracy measures the set of images that are classified correctly by crack type. In contrast, the recall and precision scores measure the ability of the model to identify concrete cracks correctly among all images classified by crack type and among all images that respectively contain cracks or not. An F1 score provides a balanced summary of the model's precision and recall performance.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FN} \tag{2}$$

$$\text{F1}_{score} = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

2.7 Robot Wall Climbing Design

In the robot design, we use an Electric Ducted Fan (EDF) which functions to activate the adhesion mechanism in the chamber. The adhesion mechanism on a wall climbing robot functions to enable the robot to stick and move on vertical or sloping surfaces. We conducted experiments with various parameters and conditions that affected the performance of the adhesion mechanism and a series of experiments to evaluate how changes in the gap height, EDF propeller speed, and affect the adhesion and efficiency of the mechanism. The experimental setup to optimise the negative pressure adhesion mechanism parameters, as shown in Figure 9.

This experimental setup involves a test arm that holds the adhesion mechanism. This arm is connected to a guide screw driven by a stepper motor, allowing adjustment of the gap height inside the chamber with an accuracy of up to ± 0.01 mm. The gap height of the chamber is controlled by an Arduino microcontroller, which serves as a data acquisition system and a throttle signal generator. This throttle signal is sent in the form of a Pulse Width Modulation (PWM) signal, which controls the speed of the EDF propeller. This throttle signal is then used by the Electronic Speed Controller (ESC) to operate the EDF propeller. In other words, this setup allows precise control of the gap height and EDF propeller speed, which is important for optimising the performance of the adhesion mechanism.

Following the optimisation of the chamber parameters for the negative pressure-thrust adhesion mechanism, the subsequent task was the development of the robot's body. The objective of this phase was to include the enhanced adhesion mechanism into a reliable and effective robotic system designed to travel the wall. The design procedure involved considering the robot's structural integrity, mobility, and control mechanisms to guarantee its efficiency in traveling vertical surfaces and carrying out accurate inspection tasks. The wall-climbing robot design is shown in Figure 10.

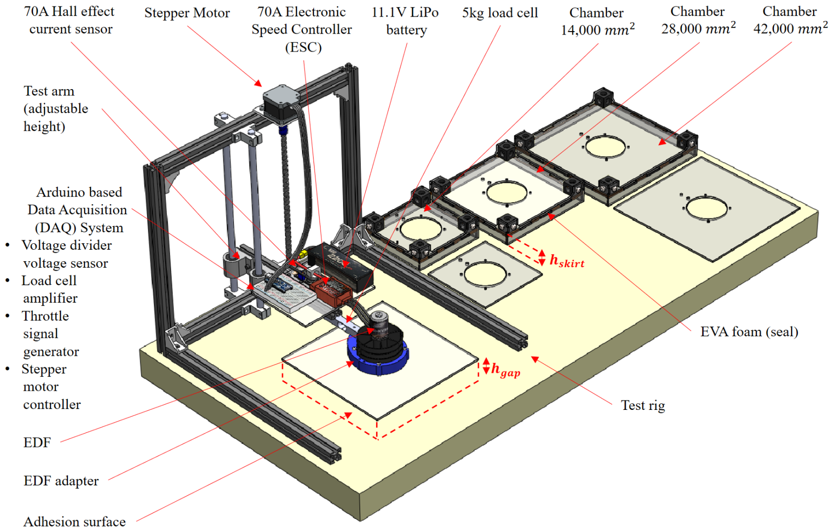


Figure 9. Electric ducted fan (EDF) evaluation.

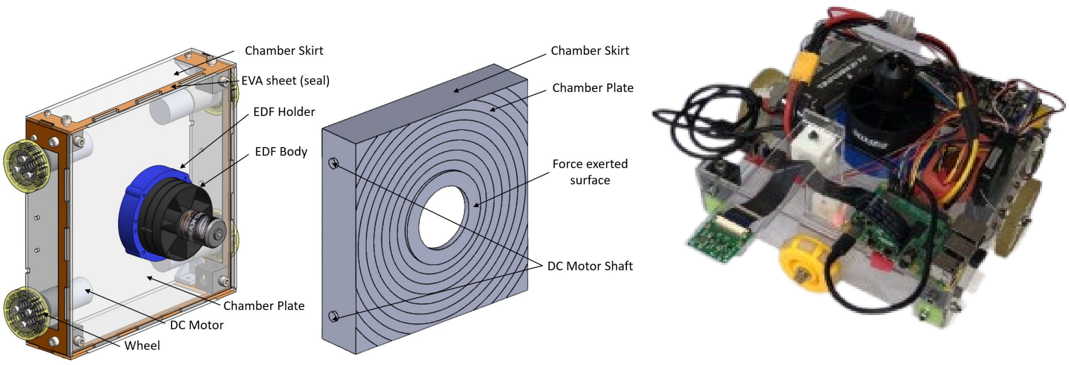


Figure 10. Wall climbing robot design.

3. RESULTS AND DISCUSSION

3.1 Confusion Matrix

In this research, the performance of classifiers was evaluated for a multiclass classification task, distinguishing between four labels, which are : label 0 is no crack, label 1 is a crocodile crack, label 2 is a transverse crack, and label 3 is longitudinal crack. The results were visualised using confusion matrices, which provide a detailed breakdown of classifier performance by showing the number of correct and incorrect predictions for each class. The confusion matrix is shown in Figure 11.

SVM is particularly good for concrete crack detection based on the true positive ratios stated in the analysis. The second highest score is Random Forest, then followed by Decision Tree. The last is followed by KNN. SVM is a method used to classify data points into different categories that best separates different groups of data. In scenarios with complex data patterns, it aligns with the complex nature of concrete crack detection, where suitable multiple variations in crack patterns can be accurately identified [23]. The accuracy of each classifier is in line with the confusion matrix. It can be seen that the average accuracy by SVM is 87%, followed by a random forest accuracy of 80%. The third place is Decision Tree, and the fourth is KNN. The accuracy of the model can be shown in Figure 12, and the recall, precision, and F1-Score are shown in Table 1.

Based on Table 1, the four classifiers are used to detect the crack with an evaluation based on precision, recall, F1-score, and accuracy. The Decision Tree classifier demonstrated a balanced performance with a moderate overall accuracy of 64%. It excelled in identifying "Not Crack" instances with a recall of 90% but showed lower performance for "Crocodile Crack" with a recall of 45%, indicating difficulty in correctly identifying this class. The SVM classifier yielded the highest accuracy rate of 87%. The model was highly precision, with 95% for "Not Crack" category and 100% for recall. This shows that SVM is exceptionally efficient in classifying between different varieties of cracks and without cracks, and it also classifies cracks based on the types of cracks. The Random Forest classifier also showed strong performance, with an accuracy of 80%. It performed well in classifying "Not Crack" with a precision of 80% and recall of 98% and "Longitudinal Crack" with precision of 88% and recall of 81%, making it a reliable alternative to SVM. However, it faced challenges with the "Crocodile Crack" class, achieving a lower recall of 58%. The KNN classifier posed a significantly low accuracy of 37%. It was especially weak in the "Crocodile Crack" class, not correctly classifying. It can be seen from precision and recall that both are 0%. Although it yielded a perfect recall of 100% for "Not Crack", its precision was very low, 26%, and therefore, a very low F1-Score of 41%. This poor performance indicates that KNN is unsuitable for this crack detection task.

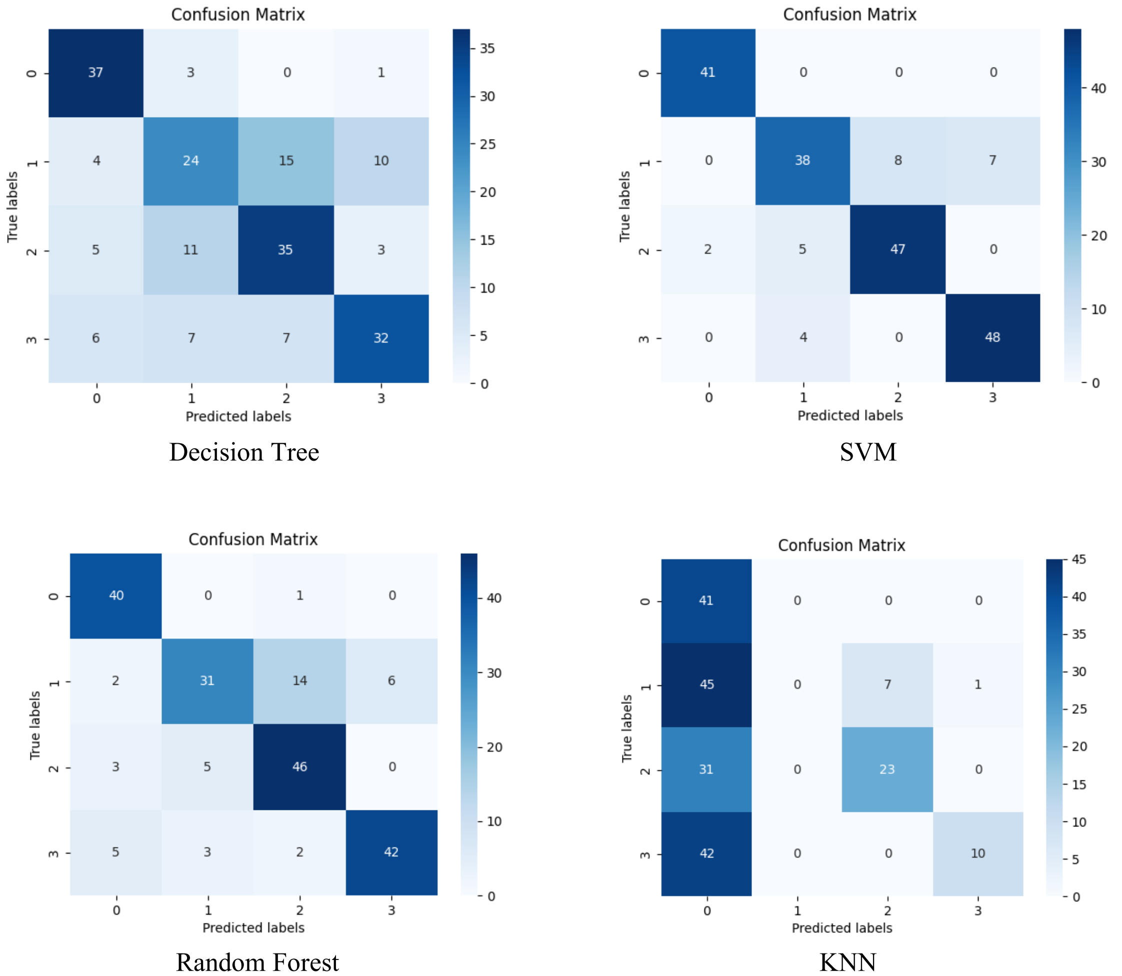


Figure 11. The confusion matrix evaluation.

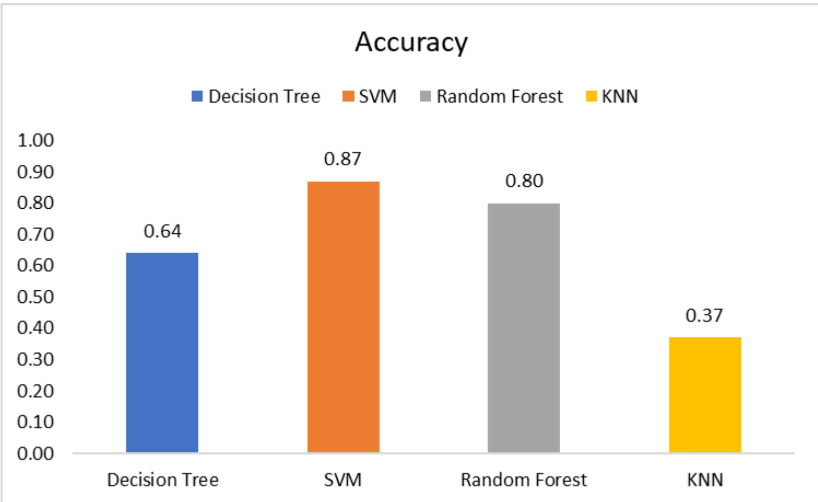


Figure 12. The average comparison for classification accuracy.

Table 1. Result of evaluation matrix.

	DecisionTree			SVM			Random Forest			KNN		
Classification	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**	**Precision**	**Recall**	**F1-Score**
Not Crack	0.71	0.90	0.8	0.95	1	0.98	0.8	0.98	0.88	0.26	1	0.41
Crocodile Crack	0.53	0.45	0.49	0.81	0.72	0.76	0.79	0.58	0.67	0	0	0
Transverse Crack	0.61	0.65	0.63	0.85	0.87	0.86	0.73	0.85	0.79	0.77	0.43	0.55
Longitudinal Crack	0.70	0.62	0.65	0.87	0.92	0.9	0.88	0.81	0.84	0.91	0.19	0.32
Accuracy			**0.64**			**0.87**			**0.80**			**0.37**

3.2 Detection Results

The detection results showed that SVM could detect all crack orientations, followed by Otsu thresholding for segmentation, which added Euclidian distance to measure the crack size. Figure 13 shows that the detection can differentiate surfaces with no cracks. Figure 14 shows the detection of longitudinal cracks. Figure 15 shows transverse crack detection. The last one is the detection of crocodile crack in Figure 16. Figure 17 illustrates the process of real-time crack detection.

Figure 13. The no-crack detection results.

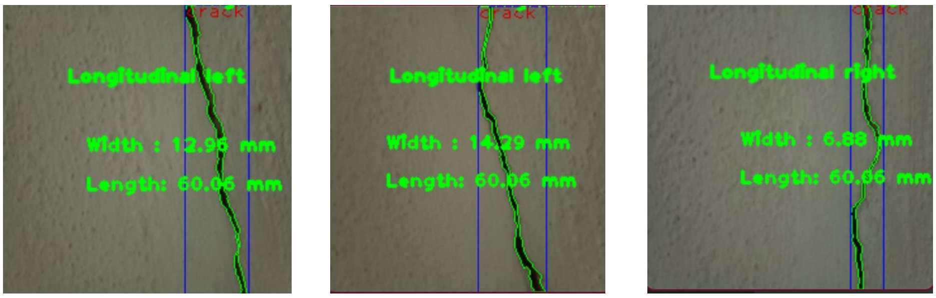


Figure 14. Longitudinal crack detection results.

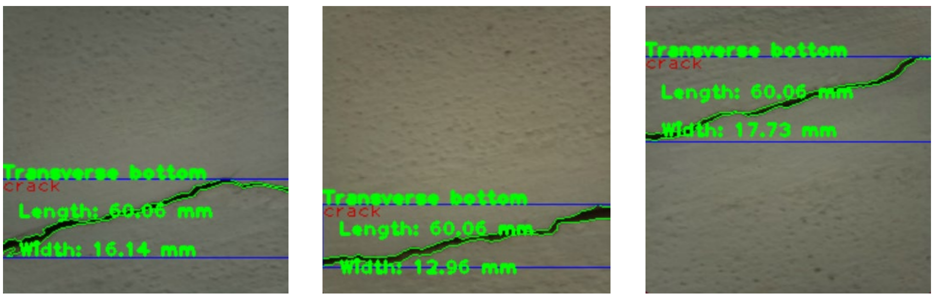


Figure 15. Transverse crack detection results.

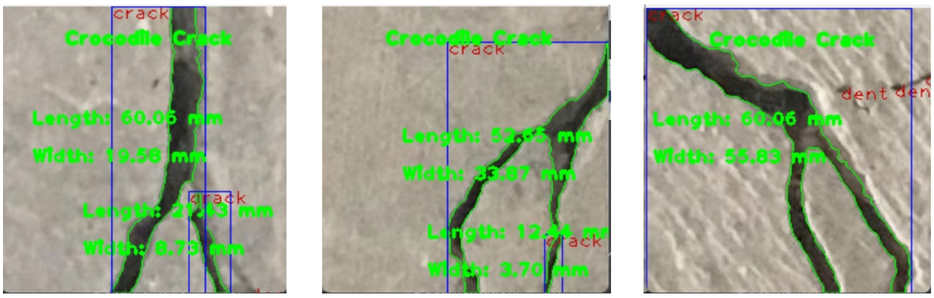


Figure 16. The crocodile crack detection results.

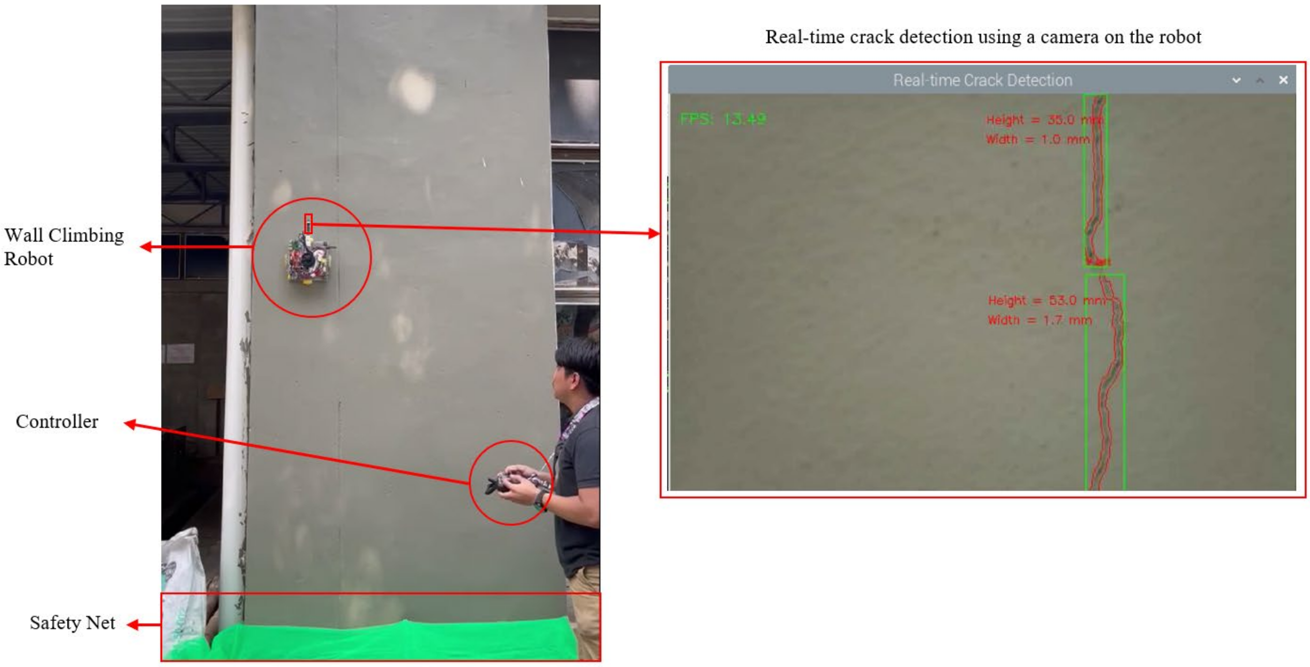


Figure 17. The process of detecting cracks in real-time.

4. CONCLUSION AND LIMITATION

The study was able to prove the efficiency of a wall-climbing robot with EDF and a camera for identifying different forms of cracks in concrete structures. The comparative analysis of the classifiers revealed that the SVM classifier was the best because it provided the highest accuracy and precision for differentiating the cracked and the non-cracked surfaces. The Decision Tree and Random Forest classifiers also gave good results, while the K-Nearest Neighbors (KNN) classifier was not suitable for this task. Despite the promising results, several limitations were identified:

- Detection of Tiny Cracks: It was not very efficient in extracting the tiny cracks due to interferences and noises in the background. This interference can make measuring the tiny crack features difficult, so it cannot properly detect crack orientation and impact measurement of crack size, it shown in Figure 18.
- Environmental Factors: Figure 19 shows that the robot's position could also affect its performance because changes in lighting and texture of the surface could increase the amount of noise and decrease its ability to detect.

These limitations could be alleviated in future work, which would also aid the robot in detecting even tiny cracks and overall enhance the general classification rate.

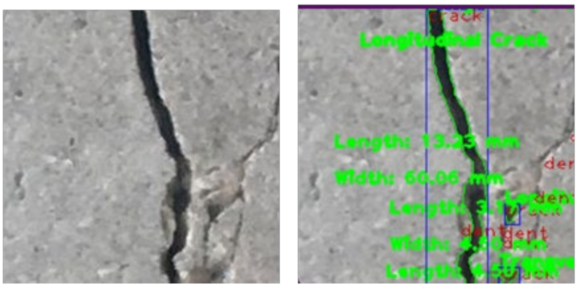


Figure 18. Tiny crack fails to detect.

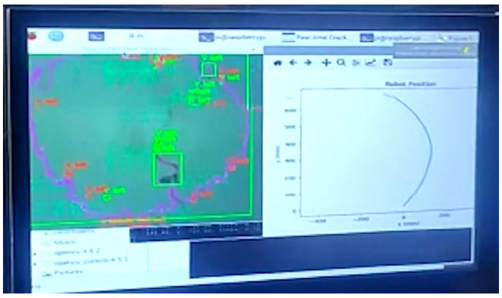


Figure 19. Low lighting condition.

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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