


PAPER

Mobile Deep Learning Framework for Automated Concrete Surface Crack Detection and Assessment on Construction Sites

Mohd Nasrun Mohd
Nawi¹ (✉), Md Azree
Othuman Mydin²,
A.Q. Adeleke³,
Rafikullah Deraman⁴ ,
Nur Amalina Mohamad
Zaki⁵, Rusman Ghani¹

¹Disaster Management
Institute, Universiti Utara
Malaysia, Kedah, Malaysia

²Universiti Sains Malaysia,
Penang, Malaysia

³Wells BlueBunny, Iowa,
IA, USA

⁴Universiti Tun Hussein Onn
Malaysia, Johor, Malaysia

⁵Universiti Malaysia
Terengganu, Terengganu,
Malaysia

nasrun@uum.edu.my

ABSTRACT

Nowadays, there are an increasing number of historic high-rise civil buildings worldwide, most of which are made of concrete. Concrete can lose strength due to environmental factors and constant loading. Consequently, the external surface of the structure may be damaged (crack and spall). If these anomalies are not looked into and fixed, the structural integrity could be compromised. Therefore, crack detection is essential when inspecting building structures to evaluate their safety. To ensure the longevity and reliability of structures, it is crucial to have professionals do building inspections on a regular basis. Traditionally, building inspections have been carried out using both human-based visual inspection techniques and deep learning (DL) techniques, which have recently demonstrated remarkable success in mobile edge integration. By integrating IoT-enabled sensors and cameras via a mobile application that acts as a real-time data gateway, this system enables the automatic assessment and detection of concrete surface cracks on construction sites. To achieve this, the study presents a mobile deep learning framework for automated concrete surface crack detection and assessment on construction sites (MDLACS-CDACS). The MDLACS-CDACS model undergoes data preprocessing, feature extraction, detection, and classification. A set of experiments was conducted to validate the MDLACS-CDACS techniques for inspectors, offering an effective way to measure the degree of damage of cracks found in image-based assessments. The study obtained an accuracy of 97.85% in damage classification without overfitting. The suggested MDLACS-CDACS outperforms state-of-the-art methods in balancing efficiency and accuracy, and real-time on-site inspection is made possible by its inference speed on edge devices.

KEYWORDS

crack detection, deep learning (DL), concrete surface, ResNet, YoLov8, cracks

Nawi, M. N. M., Mydin, M. A. O., Adeleke, A. Q., Deraman, R., Zaki, N. A. M., Ghani, R. (2026). Mobile Deep Learning Framework for Automated Concrete Surface Crack Detection and Assessment on Construction Sites. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(3), pp. 83–94. <https://doi.org/10.3991/ijim.v20i03.60067>

Article submitted 2025-10-03. Revision uploaded 2025-12-01. Final acceptance 2025-12-05.

© 2026 by the authors of this article. Published under CC-BY.

1 INTRODUCTION

Concrete is a common material used in the construction of buildings and other infrastructure [1]. Over time, material deterioration, overloading, and severe environmental conditions cause concrete structures to deteriorate.

Cracks, which can vary in size from micro-cracks to macro-cracks, are the earliest sign of trouble in these structures [2]. The concrete structure may get weaker and lose structural integrity as the cracks spread [3]. These cracks allow water and caustic substances to seep into the concrete. Rebar corrosion may occur when the cracks get to the level of the rebar. Corrosion can lead to concrete delamination and spalling [4], which compromises the structure's serviceability and safety. Finding cracks in concrete structures is essential for assessing their state and identifying any damage. Determining the best repair technique to avoid significant damage and guarantee public safety requires assessing the depth of the crack [5].

Manual visual inspection of concrete surfaces is typically used to assess concrete constructions. However, it is labor-intensive, time-consuming, and puts inspectors' safety at risk. This strategy is also influenced by the skills, expertise, and experience of the engineers in charge of the test. Modern digital image processing, ML, and sophisticated deep learning (DL) techniques could reduce the limitations of traditional visual inspection with the quick advancement of drone technology. Highly movable [6], stable, and high-performance drones have been made possible by mobile and drone technologies, and they are widely utilized to conduct routine inspections of civic infrastructures. Drones improve the results of damage identification by enabling us to take pictures close to surface damage in actual civil engineering structures [7].

In drone-based applications, ML and DL methods are becoming more popular than traditional digital image processing methods for detecting concrete surface deterioration. Unmanned aerial vehicles and ML techniques have been investigated as automated inspection techniques to get around these restrictions [7]. The benefits of automation in inspection include reduced labor costs, increased efficiency, and a lower chance of workplace accidents. The benefits of automation in inspection include increased efficiency, reduced labor costs, and a lower chance of workplace accidents [8].

Numerous real-world applications have used deep learning models for fracture width estimation. For example, crack width estimate algorithms are being used more frequently in drone-based inspection systems and mobile apps to provide on-site evaluations of concrete buildings. Using pre-trained deep learning models, these systems can take pictures of concrete surfaces and quickly determine the size and severity of any cracks they find. This lessens the need for human inspection and allows for real-time decision-making. Furthermore, structural health monitoring systems for bridges, tunnels, and dams have incorporated crack width estimating models. These devices provide continual information on the width and severity of cracks by continuously monitoring important structural sections [9, 17]. These technologies assist engineers in identifying any problems early on, enabling preventative maintenance and lowering the possibility of catastrophic failure by automating the crack measurement procedure.

This study presents a mobile deep learning framework for automated concrete surface crack detection and assessment on construction sites (MDLACS-CDACS). The MDLACS-CDACS model undergoes data preprocessing, feature extraction, detection, and classification. A set of experiments was conducted to validate the MDLACS-CDACS techniques for inspectors, offering an effective way to measure the degree of damage of cracks found in image-based assessments.

2 LITERATURE REVIEW

Kumar et al. [10] utilize the edge computing concept to suggest a real-time multi-drone damage detection method for high-rise civil structures utilizing YOLOv3, one of the cutting-edge deep learning models. The proposed method leverages Jetson-TX2 as a hardware platform to run YOLOv3 and is implemented using Pixhawk's hardware standards-based open-source hexacopter drone. If damage is detected during a coordinated survey, the Jetson-TX2 on-board, after processing, transmits only the damage-related data via the Wi-Fi channel to the ground-based server. A dataset of 800 (480×480 pixel) photographs of various damage kinds that were gathered from various CSIR-CEERI, Pilani structures is used to assess our suggested system. The upgraded YOLOv3 classifier model is tested and trained through manually annotated images. Consequently, the suggested method can process a picture in 0.033 seconds and provides dependable performance with an accuracy of 94.24%.

Akgül [11] In order to identify and categorize cracks in building structures, nine distinct models that have demonstrated notable success in the AI field are presented. Additionally, by adding auxiliary layers and block cutting to the DenseNet169 and MobileNetV2 model structures, a novel fusion model structure known as Mobile-DenseNet has been suggested. Cracks in concrete constructions were categorized using this suggested model structure. In order to identify and categorize cracks in concrete structures, an image dataset of the concrete surface was utilized. The suggested Mobile-DenseNet model achieved a 99.87% success rate in identifying fractures on the concrete surface. In the investigation, the suggested model performed better in terms of transaction volume, density, features, complexity, and success accuracy than the conventional pre-trained model structures.

Laxman et al. [12] designed a comprehensive automatic crack depth evaluation and detection system for concrete structures through images taken from portable devices. First, to detect cracks on a concrete surface automatically, a binary-class CNN model was created. Second, an incorporated CNN model was constructed to predict the depth of the fractures automatically by merging regression models (XGBoost and RF) with convolutional feature extraction layers. A reinforced concrete (RC) slab has been used to validate the suggested framework. The techniques are dependable and precise for automated crack assessment, which could aid in calculating the state of a concrete structure and choosing proper repair techniques, according to the results.

3 RESEARCH METHODS

The study presents an MDLACS-CDACS technique. The MDLACS-CDACS model undergoes data preprocessing, feature extraction, detection, and classification.

3.1 Dataset description

The dataset employed in the study includes 20,000 high-resolution photos of concrete surfaces. From uncracked concrete surfaces to those with cracks of various intensities, these pictures depict a wide variety of situations. With a resolution of 227×227 pixels, each image in the dataset provides a thorough view that is essential for identifying concrete cracks. The dataset's images are methodically divided into "Normal" and "Crack" subsets. Images of concrete surfaces with obvious fissures are included in the "Positive" subset, which illustrates the difficulties frequently found in actual concrete constructions. On the other hand, images of normal concrete

surfaces make up the “Negative” subset, which aids in training the model to identify surfaces devoid of flaws. Figure 1 displays a collection of sample photos.

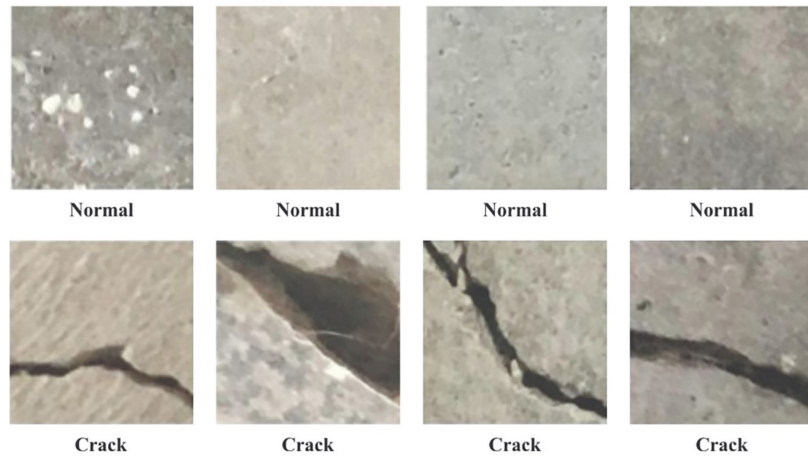


Fig. 1. Sample images of normal and crack datasets

Additionally, the uniformity of the resolution across photos ensures that the model receives consistent input, eliminating any biases or disparities that would result from different image sizes. The dataset creates a balanced training process by providing an equal amount of “Normal” and “Crack” images at a constant resolution. The dataset’s large image collection guarantees a consistent training procedure, which increases the model’s efficiency and generalization skills in real-time situations. The working procedure of the MDLACS-CDACS technique is given in Figure 2.

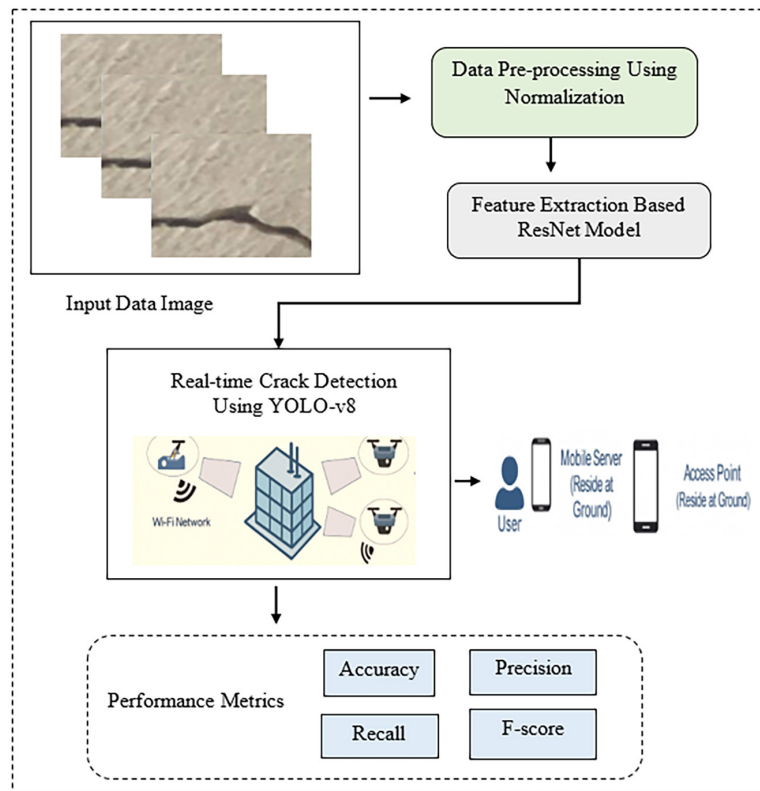


Fig. 2. Working procedure of the MDLACS-CDACS technique

3.2 Normalization

The overall pixel values, which ranged from 0 to 255, were transformed into a scale between 0 and 1 before the photos were fed into the ResNet model [13]. Particularly for ResNet, this kind of normalization guarantees quicker convergence during training and aids in retaining consistent weight updates. The following equation was used to apply normalization in this study:

$$\text{Normalized Pixel Value} = \frac{\text{Original Pixel Value} - \text{Minimum Pixel Value}}{\text{Maximum Pixel Value} - \text{Minimum Pixel Value}} \quad (1)$$

The study's dataset has a maximum pixel value of 255 and a minimum pixel value of 0. As a result, the normalization equation can be reduced to the following:

$$\text{Normalized Pixel Value} = \frac{\text{Original Pixel Value}}{255} \quad (2)$$

Regardless of the original lighting or capture parameters, every image is converted to a uniform scale. The ResNet can learn features more efficiently with more consistent input, improving generalization and possibly increasing accuracy during testing and validation.

3.3 Feature extraction-based-ResNet

The primary stage in data analysis is feature extraction. Prior to the feature extraction, the input data was subjected to a filter or statistical techniques for use in the subsequent processing stages. The usage of ResNet has seen a revolutionary evolution in terms of performance and the amount of data that can be processed with the advent of machine and DL approaches. Convolutional neural networks (CNNs), which are also utilized for feature extraction, were then developed to enable work on large-scale data sets. A CNN network is not chosen at random for feature extraction or any other component of a DL model.

Therefore, the objective task and its complexity may have an impact on how such a model is implemented. Certain suggested networks go on to become well-known networks utilized in various fields of data analysis [14]. The well-known network or architecture used for feature extraction is called a backbone. It has been trained on numerous other tasks and proven to be effective. Every backbone employed in DL models is described in detail in this section. Each backbone used in deep learning models is described in detail in this section. Residual neural network (ResNet) is a CNN-based model that introduces residual networks, in contrast to the prior CNN architecture. Robust to noise, illumination changes, and surface textures, it automatically extracts high-level and hierarchical characteristics from photographs of concrete surfaces. ResNet is made up of recurrent units or skip connections between convolutional and pooling layer blocks. Additionally, batch normalization comes after the block. Semantic segmentation and object detection are two common uses for ResNet-50 and ResNet-101. Other deep learning architectures, such as R-FCN and Faster RCNN, are also utilized with ResNet.

3.4 YOLOv8

YOLOv8 provides real-time object identification and segmentation. Instead of predicting the size and location of the anchor box, YOLOv8 develops an anchor free-based detection technique that directly predicts the width-to-height ratio and center point of the targets. This technique might decrease the anchor box number while improving detection accuracy and speed. An enhanced MHSA and TA-based YOLOv8 object detection and segmentation method. The Neck, Backbone, and Head are the three main parts of the suggested YOLOv8 object segmentation network topology. Among them, fundamental data augmentation techniques like gaussian-noise, rotation, and flipping are performed prior to importing picture data into Backbone. Extracting feature information from the input image that corresponds to the target area is Backbone's main responsibility. Conv, C2f, and SPPF are used to extract the features of the target area after the image data is imported into Backbone. The features attained are then processed through the MHSA network to extract more valuable feature information and increase the feature weight of the target area. The feature fusion acts as the main function of the neck [15].

Three distinct scale network branches are displayed in the backbone input to the neck section, involving the backbone end feature branches following feature improvement with MHSA. To identify and segment the target areal feature, the triplet attention part receives the three feature branches that result from the feature fusion of the neck before being fed into the head part again. The primary output information is the location and type of cracks. A thorough overview of each module is provided below. The crack segmentation creation process in our proposal uses an input image size of 448 by 448. When entering image data, the YOLOv8 employs the same data augmentation method as YoLov5, which includes gray-scale, random crop, blur, median blur, and CLAHE. The proposed YoLov8 uses the Darknet53 network as its foundation and replaces each C3 with a C2f component. Inspired by both the C3 component and ELAN, the C2f component is introduced to extract more gradient flow information while being lighter than the C3 component. Additionally, there are now additional split operations and jumper connections thanks to C2f. Due to unevenly shaped cracks, some categories in the Crack segmentation model utilized in this study are ambiguous. This work uses the MHSA attention mechanism to improve the feature branches output by the backbone end in order to guarantee that the model extracts more feature data. Q, K, and V are the three matrix operations that make up a standard self-attention mechanism. The foundation of these operations is self-operation. Self-operation is at the core of these operations. The MHSA is an enhanced version of the conventional self-attention mechanism, where each attention action can gather useful feature information from several dimensions through grouping. The Neck section adopts the triplet attention structure. In contrast to YOLOv5 and YOLOv6, the upgraded YOLOv8 inserts the feature map output from various backbone stages directly into the up-sampling stage by substituting C2f for the C3 module and RepBlock of the Neck.

Before upsampling, the 1x1 convolution is likewise eliminated. The fusion and application of feature layer data at different scales are enhanced by the use of TA, a feature fusion technique. While learning intricate spatiotemporal short- and long-range dependencies, this TA can maintain computational efficiency. The proposed YOLOv8 component offers two significant enhancements

over YOLOv5: (1) employing the mainstream decoupling head structure to separate classification and segmentation, and (2) moving from anchor-based to anchor-free.

4 RESULT AND DISCUSSION

The training and validation subsets of the dataset were separated. The training set received up to 80% (30,000) of the images, whereas the validation set received 20% (7000). To avoid overfitting and to guarantee the model's performance metrics, partitioning is crucial. To assess the effectiveness of several thresholding techniques and the MDLACS-CDACS model's performance in concrete crack detection, a thorough comparison was carried out. Figure 3 displays the training (TRAC) and validation accuracy (VLAC) plot [16]. The majority of thresholding methods were found to have strikingly comparable outcomes. These techniques regularly attained an accuracy of about 97% after training for ten epochs. The accuracy of 96% obtained by the method utilizing grayscale images without any thresholding shows how efficient thresholding is in improving detection precision and image quality. Experimental validation was carried out to assess the accuracy and performance of the crack-detecting algorithm created in this study. A Nikon D5100 camera with a resolution of 4928×3264 pixels was utilized to take the test image. By measuring the distance between the camera and the concrete surface using a laser distance measure, which revealed a distance of 518 mm, the accuracy of taking this picture was guaranteed. With a focal length of 18 mm and an image sensor width of 23.6 mm, the camera settings were suitably modified.

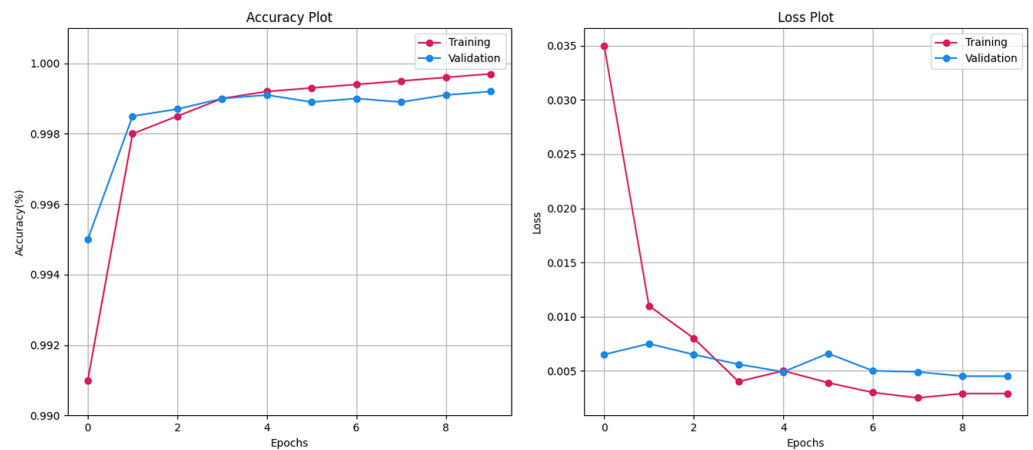


Fig. 3. Accuracy and loss curves of the MDLACS-CDACS model under the training-validation dataset

Table 1. Details of dataset

Classes	No. of Samples
Normal	340653
Crack	14596
Total No. of Samples	474661

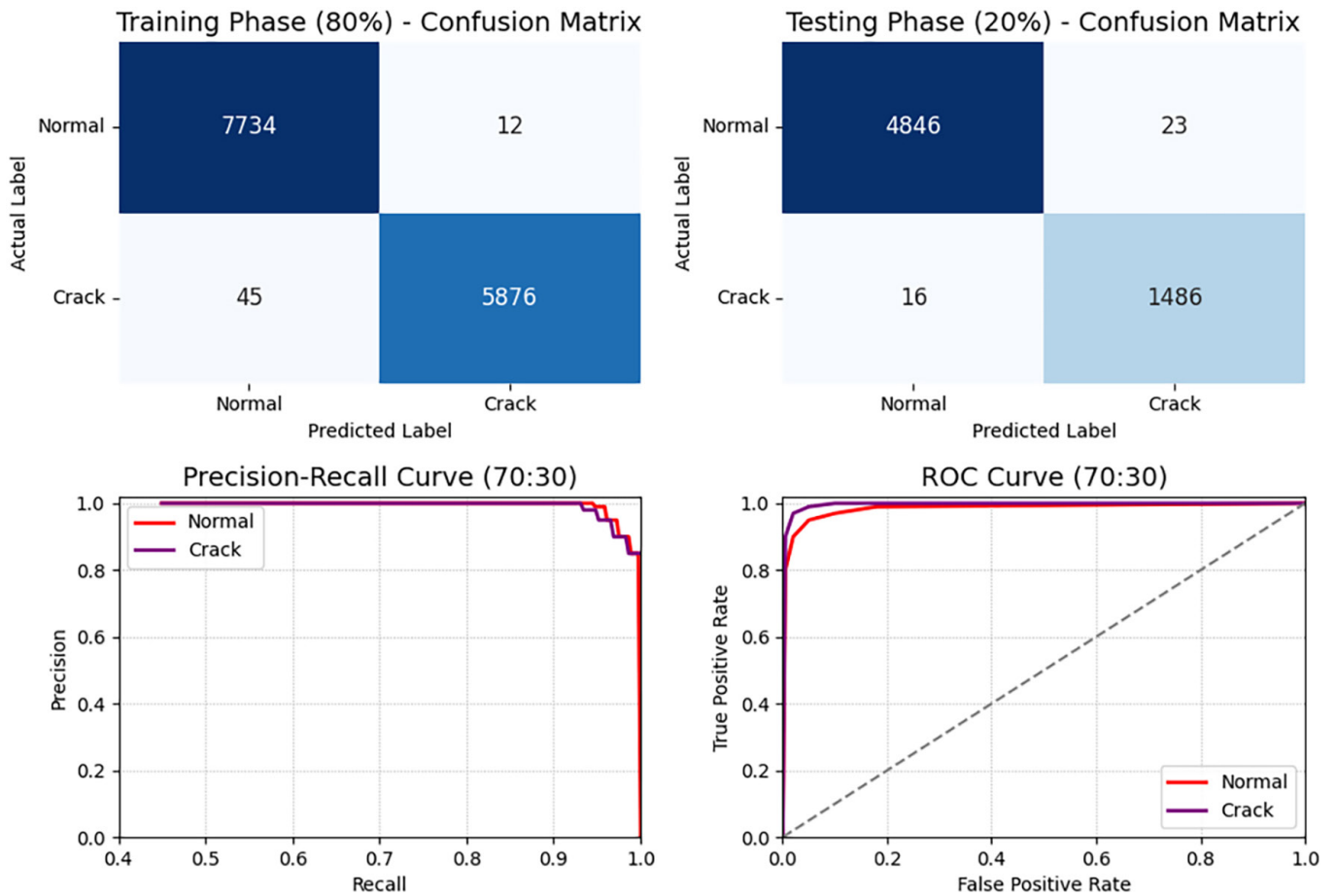


Fig. 4. Confusion matrix with PR and ROC curve of MDLACS-CDACS under 70:30 TRPH/TSPH

Figure 4 shows the confusion matrices produced by the MDLACS-CDACS method on 70% TRPH and 30% TSPH, as well as the classification performance of the method under the crack detection dataset. The experimental outcomes showed that both class labels were correctly identified and classed by the MDLACS-CDACS technique. Similarly, Figure 4 displays the PR and ROC analysis of the MDLACS-CDACS method. The graph demonstrated that the MDLACS-CDACS method produced effective outcomes with the highest ROC values on two labels.

Table 2. Crack classifier outcome of the MDLACS-CDACS method at 70:30 of TRPH/TSPH

Classes	$Accu_y$	$Prec_n$	$Reca_t$	F_{Score}
Normal	96.31	95.05	93.06	96.06
Crack	95.25	94.42	91.29	94.36
Average	97.50	96.82	93.46	97.53
Normal	94.35	83.06	80.12	88.09
Crack	95.38	95.52	87.34	89.43
Average	96.09	94.07	90.63	90.21

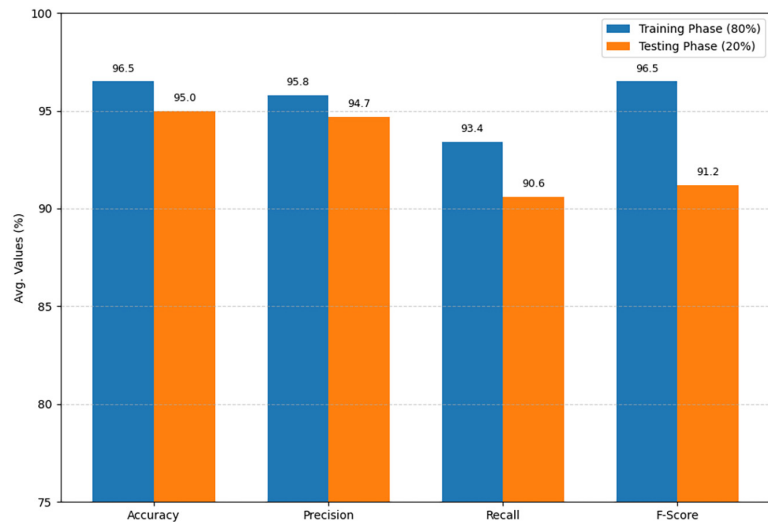


Fig. 5. Average of MDLACS-CDACS approach under 70:30 TRPH/TSPH

Table 3. Comparison analysis of MDLACS-CDACS model with other techniques

Algorithms	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
MDLACS-CDACS	97.79	96.90	97.78	97.82
Mobile-DenseNet	97.20	96.78	96.80	94.20
KNN	96.32	92.06	96.03	95.11
RNN	96.38	95.22	94.50	95.89
YOLOv3	95.80	94.83	93.47	95.56

A brief comparison of the MDLACS-CDACS algorithm is shown in Table 3. A comparison of the MDLACS-CDACS technique’s $accu_y$, $prec_n$, $reca_p$, and F_{score} results are shown in Figure 6. According to the findings, the MDLACS-CDACS approach outperforms other methods.

Based on $accu_y$, the MDLACS-CDACS approach, it offers higher $accu_y$, $prec_n$, $reca_p$, and F_{score} outcomes of 97.79%, 96.90%, 97.78% and 97.82%, while the Mobile-DensNet, KNN, RNN, and YOLO_v3 provide lower $accu_y$, $prec_n$, $reca_p$, and F_{score} correspondingly.

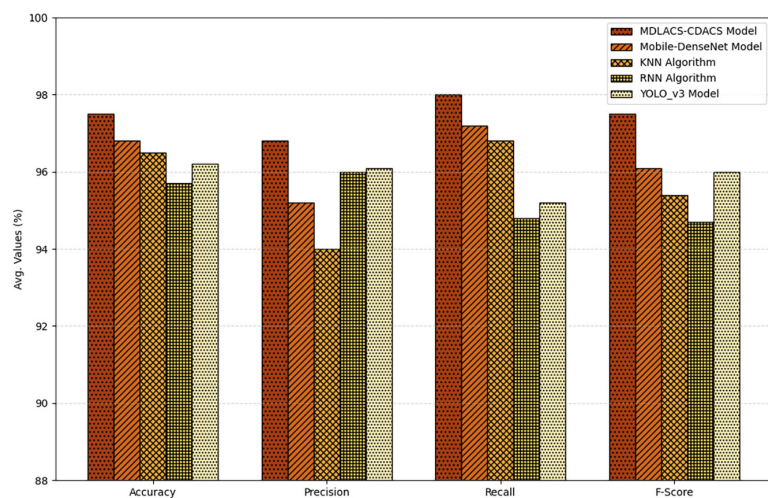


Fig. 6. Comparative analysis MDLACS-CDACS technique with other existing approaches

5 CONCLUSION

In this study, we present an MDLACS-CDACS. The MDLACS-CDACS model undergoes data preprocessing, feature extraction, detection, and classification. A set of experiments was conducted to validate the MDLACS-CDACS techniques for inspectors, offering an effective way to measure the degree of damage of cracks found in image-based assessments. The study obtained accuracy of 97.85% in damage classification without overfitting. The suggested MDLACS-CDACS outperforms state-of-the-art methods in balancing efficiency and accuracy, and real-time on-site inspection is made possible by its inference speed on edge devices.

6 ACKNOWLEDGEMENT

The authors would like to express their gratitude to the Universiti Negeri Padang and Universiti Utara Malaysia for their support in completing this research (SO Code: 21308).

7 REFERENCES

- [1] P. S. Chakurkar, D. Vora, S. Patil, S. Mishra, and K. Kotecha, "Data-driven approach for AI-based crack detection: Techniques, challenges, and future scope," *Frontiers in Sustainable Cities*, vol. 5, p. 1253627, 2023. <https://doi.org/10.3389/frsc.2023.1253627>
- [2] R. A. Swarna, M. M. Hossain, M. R. Khatun, M. M. Rahman, and A. Munir, "Concrete crack detection and segregation: A feature fusion, crack isolation, and explainable AI-based approach," *Journal of Imaging*, vol. 10, no. 9, p. 215, 2024. <https://doi.org/10.3390/jimaging10090215>
- [3] M. Mirbod and M. Shoar, "Intelligent concrete surface cracks detection using computer vision, pattern recognition, and artificial neural networks," *Procedia Computer Science*, vol. 217, pp. 52–61, 2023. <https://doi.org/10.1016/j.procs.2022.12.201>
- [4] O. M. O. Abdalla, A. Encalada-Dávila, and M. S. Ekole, "Performance evaluation of AI and traditional techniques for crack detection on concrete structures," *World Journal of Science, Technology and Sustainable Development*, vol. 20, no. 3, pp. 279–293, 2025. <https://doi.org/10.47556/J.WJSTSD.20.3.2025.5>
- [5] K. Sarkar, A. Shiuly, and K. G. Dhal, "Revolutionizing concrete analysis: An in-depth survey of AI-powered insights with image-centric approaches on comprehensive quality control, advanced crack detection and concrete property exploration," *Construction and Building Materials*, vol. 411, p. 134212, 2024. <https://doi.org/10.1016/j.conbuildmat.2023.134212>
- [6] M. Shahin *et al.*, "Improving the concrete crack detection process via a hybrid visual transformer algorithm," *Sensors*, vol. 24, no. 10, p. 3247, 2024. <https://doi.org/10.3390/s24103247>
- [7] S. S. R. Krishnan *et al.*, "Comparative analysis of deep learning models for crack detection in buildings," *Scientific Reports*, vol. 15, no. 1, p. 2125, 2025. <https://doi.org/10.1038/s41598-025-85983-3>
- [8] Y. Shao, L. Li, J. Li, X. Yao, Q. Li, and H. Hao, "Advancing crack detection with generative AI for structural health monitoring," *Structural Health Monitoring*, 2025. <https://doi.org/10.1177/14759217251369000>
- [9] K. B. Blay, C. Gorse, C. Goodier, J. Starkey, S. Hwang, and S. H. P. Cavalaro, "Artificial intelligence (AI) for reinforced autoclaved aerated concrete (RAAC) crack defect identification," *International Journal of Building Pathology and Adaptation*, 2025. <https://doi.org/10.1108/IJBPA-05-2024-0104>

- [10] P. Kumar, S. Batchu, and S. R. Kota, "Real-time concrete damage detection using deep learning for high rise structures," *IEEE Access*, vol. 9, pp. 112312–112331, 2021. <https://doi.org/10.1109/ACCESS.2021.3102647>
- [11] I. Akgül, "Mobile-DenseNet: Detection of building concrete surface cracks using a new fusion technique based on deep learning," *Heliyon*, vol. 9, no. 10, p. e21097, 2023. <https://doi.org/10.1016/j.heliyon.2023.e21097>
- [12] K. C. Laxman, N. Tabassum, L. Ai, C. Cole, and P. Ziehl, "Automated crack detection and crack depth prediction for reinforced concrete structures using deep learning," *Construction and Building Materials*, vol. 370, p. 130709, 2023. <https://doi.org/10.1016/j.conbuildmat.2023.130709>
- [13] J. Zhang and T. Bao, "An improved resnet-based algorithm for crack detection of concrete dams using dynamic knowledge distillation," *Water*, vol. 15, no. 15, p. 2839, 2023. <https://doi.org/10.3390/w15152839>
- [14] L. Hui, A. Ibrahim, and R. Hindi, "Computer vision-based concrete crack identification using mobileNetV2 neural network and adaptive thresholding," *Infrastructures*, vol. 10, no. 2, p. 42, 2025. <https://doi.org/10.3390/infrastructures10020042>
- [15] X. Dong, Y. Liu, and J. Dai, "Concrete surface crack detection algorithm based on improved YOLOv8," *Sensors*, vol. 24, no. 16, p. 5252, 2024. <https://doi.org/10.3390/s24165252>
- [16] G. Atkin, "Concrete crack image detection," *Kaggle*, 2021. <https://www.kaggle.com/code/gcdatkin/concrete-crack-image-detection>
- [17] Y. Liao and H. Luo, "Real-time defect detection and carbon footprint visualization in green construction using mobile augmented reality and building information modeling," *International Journal of Interactive Mobile Technologies (ijIM)*, vol. 19, no. 9, pp. 92–106, 2025. <https://doi.org/10.3991/ijim.v19i09.55579>

8 AUTHORS

Mohd Nasrun Mohd Nawi specializes in the area of integrated design and construction management. He is working at the Disaster Management Institute (DMI), School of Technology Management and Logistics, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia. He holds a PhD in the field of Construction Project Management from the University of Salford, UK. As an academic and a fully qualified Building Surveyor, he has been actively involved in research and consulting work related to the areas of Industrialized (offsite) and Modern Methods of Construction, as well as Integrated Design Delivery Solutions. Integrated Project Delivery, Lean Construction, Building Information Modelling, Sustainable (Green) Construction, Life Cycle Costing, Value Management, Building Performance (e.g., Energy Management and Audit), and Management of Technology. Besides actively particularly in various academic activities, he is also a prolific author with numerous publications, particularly in the field of Construction and Technology Management (E-mail: nasrun@uum.edu.my).

Assoc. Prof. Sr. Ts. Dr. Md Azree Othuman Mydin is an accomplished academician and an expert in building surveying and technology, currently serving as the Dean of the School of Housing, Building, and Planning at Universiti Sains Malaysia, 11800, Penang, Malaysia. With over 20 years of experience in the field, he holds a BSc and MSc in Building Technology and a PhD in Civil Engineering, further solidifying his extensive academic foundation and practical expertise. Dr. Md Azree specializes in building science, with a particular focus on Malaysia's unique climate and environmental challenges. His expertise and leadership in the field position him as a key figure in advancing sustainable, resilient, and innovative property development practices that address the specific needs of Malaysia's evolving urban landscape (E-mail: azree@usm.my).

A.Q. Adeleke served as an Adjunct Associate Professor in the Department of Accounting and Business at Morningside University in Sioux City, Iowa, USA. He completed a Post-Doctoral Fellowship at the School of Surveying and Construction Innovation at Technological University Dublin from 2022 to 2023. From 2021 to 2022, he was an Associate Professor in Project Management at the International University of Malaya-Wales in Malaysia. Between 2017 and 2022, he worked as a Senior Lecturer in Project Management at Universiti Malaysia Pahang. He earned his PhD in Technology Management with a specialization in Construction Project Management from Universiti Utara Malaysia in 2016. He also holds a First Class Honours Bachelor's degree in Business Information Systems from the University of East London. Adeleke is affiliated with several professional bodies, including CABE (UK), PMI (USA), ACPM (Malaysia), and MIM (Malaysia). His research focuses on project management areas such as construction risk management, IT in projects, sustainability, IR 5.0 issues, and organizational control. He has authored books, published over 60 journal papers, and supervised multiple postgraduate and undergraduate students. Adeleke has also led research grants, held editorial and leadership roles, chaired an international conference, and provided consultancy services for various organizations (E-mail: aadekunle0@gmail.com).

Ts. Dr. Rafikullah Deraman is a Senior Lecturer at the Department of Architecture, Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn, 86400 Parit Raja, Johor, Malaysia. He also serves as the Head of the Accreditation Department for Academic Development (CAD) at Universiti Tun Hussein Onn, Malaysia. He graduated with a PhD in Construction IT from the University of Malaya in 2014. He has also been a professional technologist registered with the Malaysia Board of Technologists (MBOT) since 2017. He has almost 4.5 years of industrial working experience and 24 years of experience with educational institutions. He has been a certified internal lead auditor for UTHM since 2017 and a member of the accreditation audit panel for the Technology and Technical Accreditation Council (TTAC, MBOT) since 2020. He has been reviewing various international journal papers and serving as the program advisor for undergraduate programs at INTI International University. His research interests mainly include sustainable building materials, construction IT, construction management, and building maintenance (E-mail: rafikullah@uthm.edu.my).

Nur Amalina Mohamad Zaki is a Senior Lecturer at the Faculty of Business, Economics, and Social Development (FBESD) at Universiti Malaysia Terengganu (UMT), 21300 Kuala Terengganu, Terengganu, Malaysia. In 2007, she obtained a bachelor's degree (B.Sc.) in Business Administration with triple majors in Management, International Business, and Business Information Systems from Indiana University, Bloomington, USA. She then pursued her Master of Business Administration with a specialization in Marketing from Western Michigan University in Michigan, USA. Amalina holds a PhD in Marketing from Griffith University, Australia, awarded in 2017. She also pursued a postdoctoral degree at the University of Sydney, Australia, in 2018. Her research interests lie in the field of Digital Marketing. Currently, she holds several domestic and international research grants (E-mail: amalina@umt.edu.my).

Dr. Rusman Ghani, C.A.(M), is a Senior Lecturer at the Tunku Puteri Intan Safinaz School of Accountancy, College of Business, Universiti Utara Malaysia (UUM COB), 06010 Sintok, Kedah, Malaysia. My area of interest is Accounting and Auditing in Information Systems Environment, Mandatory and Voluntary Disclosure, Financial Accounting, and Reporting. I have work experience for over 20 years. I have industrial experience of more than 12 years. I am a Chartered Accountant of the Malaysian Institute of Accountants (MIA) (E-mail: rusman@uum.edu.my).