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RESEARCH ARTICLE

Deep Learning

Aerial crack detection in building structures using convolutional neural networks

CS Silva*, DMKI Dissanayake, RSMPW Rathnayake and NTA Sathsara
Instrumentation and Automation Technology, Faculty of Technology, University of Colombo, Pitipana, Homagama, Sri Lanka.

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Abstract: Evaluating cracks is a crucial step in preserving concrete structures. Manual visual observation of the surface is the common method for inspecting concrete cracks, but it is inherently subjective and depends on the inspectors' expertise. Moreover, it is inefficient, costly, and often hazardous when building structures are hard to reach. In structural health monitoring, unmanned aerial vehicles (UVAs) outfitted with advanced sensing and imaging technologies offer the capacity to detect and assess defects, such as corrosion and cracking, in buildings and infrastructure, thereby facilitating proactive maintenance and early hazard identification. This study presents the design and implementation of a UAV system integrating both sonar and visual sensors, aimed at detecting and classifying building cracks through deep learning techniques. The combined use of heterogeneous sensors represents a novel approach that capitalizes on their respective strengths while mitigating individual drawbacks. The detection of crack presence and depth is accomplished using sonar sensors. Visual capture is then initiated triggering the cameras only after a crack is detected by the sonar to minimize processing overhead during image analysis. The images of the cracks acquired by the vision sensors are processed by a customized convolutional neural network model which shows 99% accuracy in detecting and identifying the cracks.

Keywords: Convolutional neural network, crack detection and identification, deep learning, sonar sensors, unmanned aerial vehicle, vision sensors.

INTRODUCTION

Finding structural flaws is crucial for several reasons. Building cracks typically point to underlying structural issues, including poor foundations, settlement, or structural stress. Finding cracks enables an evaluation of the building's structural soundness and establishes whether there is a danger of collapse or failure. Manual contact measurements were traditionally used to detect cracks in structures. However, they were time-consuming and showed inconsistent results. The introduction of new technology rendered the crack analysis, more reliable and efficient, and equally important, such technology can overcome other limitations of conventional visual inspection methods. The objective of this research is to demonstrate a fully integrated system that combines custom made UAV with convolutional neural networks (CNNs) for the detection and identification of cracks in buildings

Perception modalities for crack detection

Non-imagery sensors were primarily utilized in the literature to identify building cracks. A four-point bending test was suggested by Chakraborty *et al.* (2019) to assess the implanted sensors' sensitivity to spot cracking and its spread. Babu *et al.* (2022) have proposed crack detection using ultrasound sensors to automatically detect invisible cracks in concrete structures. GSM and GPS modules were used to track the locations of cracks in concrete structures (Babu *et al.*, 2022) . The sensors are embedded in cubes and cylinders of concrete that have been combined with cement, fine sand, coarse sand, and water. The cylinders and cubes are weighed after curing, and any identified cracks are shown on an LCD screen (Babu *et al.*, 2022).

* Corresponding author (chathurika@iat.cmb.ac.lk; https://orcid.org/0000-0002-3914-5392)

The majority of automated crack detection methods use surface images captured using vision sensors such as monocular RGB cameras, an array of RGB cameras, a line-scanning camera, or 2D projections of 3D scans (Yuan *et al*., 2023). The textural, intensity, contours, and shape information extracted through these sensory images is then examined to identify cracks on buildings. However, the challenge of detecting cracks in an outdoor environment is to ensure sufficient illumination on the surface such that the contrast between cracks and the surface can be visually distinguished. Moreover, the images could also suffer from illumination imbalance due to the sensor-light setup or external factors such as shadows cast from objects such as trees and lamp posts (Yuan *et al.*, 2023).

More recently there has been an increasing trend towards using image-based methods for crack detection and analysis. These techniques involve taking pictures of the intended component and using programming to locate and categorize cracks. The methods can be categorized into two types, namely, image processing and machine learning. Velumani *et al.* (2020) establish an image processing methodology for the automated identification and examination of cracks. To enhance image quality, the suggested model uses the gray intensity correction method, specifically the min max grey level differentiation (M2GLD). Crack detection also makes use of the Otsu image binarization process. The experimental findings show that the M2GLD approach and the Otsu test work well together to identify crack faults in digital photos. Hoang *et al.* (2018) have proposed developing an automated fracture detection tool for concrete wall surfaces using edge detection methods such as Roberts, Prewitt, Canny, and Sobel. Hoang *et al.* (2022), forward an innovative method based on computer vision for detecting sealed cracks. This technique uses image processing and metaheuristic-optimized feature extraction to capture visual appearance and texture in pavement photographs. It uses the Salp Swarm algorithm and multiclass support vector machine for pattern recognition, achieving 91.33% accuracy in detecting cracks and 92.83% accuracy in sealing them. Munawar *et al.* (2021) present a review on crack detection methods based on image processing. This review provides a comprehensive analysis and comparison of these methods, highlighting the most promising automated approaches for crack detection. Similarly, Gupta and Dixit (2022) discuss the use of thresholding-based methods in crack detection. The concept of thresholding is to select the higher pixel value by the selected threshold value. These studies highlight the potential of using image-based techniques for crack detection but also emphasize the challenges posed by varying illumination conditions and the need for effective feature extraction and representation.

Moreover, integration of feature representation and classification in deep learning creates a powerful pipeline that requires minimal pre-processing of raw data, thus eliminating the need for manual feature extraction. As a result, the development of image-based deep neural network architectures has paved the way for the use of deep neural network (DNN) techniques in detecting cracks in images (Ali, *et al.*, 2021). Convolutional Neural Networks (CNNs) are a type of deep neural network that is developed primarily for processing structured grid-like data, such as images. Their design comprises numerous layers, each serving a specific purpose in extracting hierarchical representations from input data. Input layer, convolutional layer, activation function, pooling layer, fully connected layer, and output layer are some of layers exhibit in CNNs to analyse and learn from complicated visual data.

Yang *et al.* (2021) proposed to identify structural cracks. This experiment uses transfer learning on the ImageNet dataset, with a maximum of 50,020 training batches. Leaky ReLU and stochastic gradient descent are used as the activation function and optimizer. Tan *et al.* (2023) have developed an automatic crack detector using a state-of-the-art technique called deep learning mask regional network (R-CNN). The mask R-CNN algorithm segments objects in natural images, enabling efficient crack detection. According to Alzubaidi *et al.* (2021) the application of deep architectures inspired by the fields of artificial intelligence and computer vision has made a significant impact on the task of crack detection. They present a comprehensive literature review of deep learning-based crack detection studies and the contributions that they have made to the field. The studies are categorized according to the computer vision aspect and at deeper levels to facilitate exploring the studies that utilized similar approaches to address the crack detection problem. Ali *et al.* (2021) propose a convolutional neural network model for crack detection in concrete structures. According to the results, VGG-16 outperforms the other models. Słoński (2019) has compared the performance of four deep convolutional neural networks in the problem of image-based automated detection of concrete surface cracks as a binary classification problem, and it is solved by training a deep convolutional neural network on a small dataset. The classification accuracy of the best deep convolutional neural network on the testing set is about 94%. Fang *et al.* (2020) trained a deep convolution neural network (DCNN) by using an existing dataset and then retrained the architecture by using a self-created dataset of 184K images.

There are some pre-trained models such as VGG-16 (Simonyan & Zisserman, 2014), VGG-19 (Simonyan & Zisserman, 2014), and ResNet-50 (He *et al.*, 2016). The VGG-19 denotes its distinctive architectural design consisting of 19 layers (Simonyan & Zisserman, 2014). The VGG-19 model developed by the Visual Graphics Group (VGG) at the University of Oxford, represents a significant advancement in the domain of deep learning and computer vision. Unlike pre-defined architectures such as VGG and ResNet, a customized model offers the flexibility to adjust the number, type, and configuration of layers, including convolutional, pooling, and fully connected layers. This adaptability allows researchers and practitioners to design networks that precisely suit the requirements of diverse applications, enhancing performance and efficiency (Zeiler & Fergus, 2013).

Unmanned arial vehicle-based crack detection

An aerial vehicle is defined as any aircraft capable of maintaining airborne stability through the dynamic interaction of air against its lifting surfaces. This broad category of aviation encompasses airships, balloons, helicopters, and aeroplanes. Fixed-wing aerial vehicles, including UAV, primarily generate lift by propelling their wings forward. Ahmed *et al.* (2022) have conducted a comprehensive survey of recent developments in commercially available UAVs, providing insights into their structure, working methodology, flying features, and navigation control. The classification system for aerial vehicles is primarily divided into three categories: fixed-wing aircraft, rotary-wing aircraft, and hybrid UAVs. Each type has its unique set of advantages and disadvantages. Scott *et al.* (2022) provide a systematic review of predictive maintenance focused on a defence domain context, with a particular focus on the operations and sustainment of fixed-wing defence aircraft. Meanwhile, Muhammed and Virk (2023) offer a comprehensive review of studies related to rotary-wing UAVs. Sinnemann *et al.* (2022) discuss the enormous possibilities offered by the cooperation of UAVs and mobile robot manipulators (MRMs) in modern industry.

Hexacopter and quadcopter are another two classifications of UAVs. A hexacopter is equipped with six rotors, and offers superior stability, payload capacity, and flight agility compared to quadcopter variants (Shelare *et al.*, 2023). A quadcopter, also known as a quadrotor, is an aircraft equipped with four rotors on its rotor blades (Husnain *et al.*, 2023). To ensure the total torque exerted on the aircraft is zero, these rotors operate in pairs, with one pair rotating clockwise and the other counter-clockwise (Idrissi *et al.,* 2022).

In the literature, UAVs are mostly equipped with sensors for the purpose of detection of building cracks using computer vision and machine learning. N-Ho Kim *et al.* used a commercial UAV with high-resolution vision sensors for crack identification in ageing concrete bridges. The method generates a background model using point cloud data and deep learning algorithms. The UAV-based method is effective in detecting and quantifying cracks in various structures. These studies highlight the potential of UAVs and image-based computer vision in the field of crack detection (Phang *et al.*, 2021; Yang, 2023).

Previous studies in UAV-based crack detection have demonstrated the use of either visual sensors or range sensors in isolation. This research aims to synergize both sensor modalities—combining vision and range sensing—to enhance the detection and characterization of building cracks through aerial images.

MATERIALS AND METHODS

Design and development of the drone

The UAV used in this research, as shown in Figure 1, is a custom-made quad-quaptor with a flight controller consisting of TM32F411CEU6 (Black Pill) as the micro-controller. Sensors include MPU6050 for real-time angular velocity and linear acceleration measurements, BMP280 for altitude measurements based on barometric pressure, GY-271 for the measurements of the Earth's magnetic field, and a Neo6M GPS module for positioning. A FlySky FS-i6 Transmitter is used for manual control of the UAV which utilizes the i-BUS protocol to communicate between the transmitter and the flight controller. The four 850 kV brushless motors

Figure 1: Quad-quaptor developed in the research used for image acquisition

were used to generate the thrust required for flight. The drone is powered by a 3300 mAh LiPo (lithium polymer) 3S Battery. The Rev 1.3 camera features a 5-megapixel Omni-vision OV5647 sensor. It can capture still images up to 2592 x 1944 pixels, sufficient for most entry-level image capture needs. The Raspberry Pi 3B+ was integrated into the drone as the central processing unit for camera operations. The 8MP Raspberry Pi Camera and two HC-SR04 ultrasonic sensors were connected to the Raspberry Pi, to detect and identify the presence of the crack.

The HC-SR04 ultrasonic sensors, strategically positioned, continuously measured distances to nearby objects. These sensors emitted ultrasound bursts, which are reflected off the objects and returned. By analysing the time taken for the reflected ultrasound to reach the sensor, the distance was accurately determined. These distance values were crucial for real-time obstacle detection and navigation. The camera module captured visual information from the surroundings. It provided high-resolution images that aided in object recognition, scene analysis, and contextual awareness. To ensure efficient collaboration and real-time decision-making, both the distance measurements and captured images were shared with a database.

Design and development of the web application

The primary purpose of developing the web application is to enable real-time monitoring of building cracks from a ground station and share them with the relevant parties. The web application shown in Figure 2, developed using React, seamlessly integrates images captured by the Raspberry Pi and the corresponding average distances computed by the ultrasonic sensors, all of which are transmitted via Firebase. In addition, the GPS module supplies real-time location data. The web application effectively displays the received images and their corresponding distance measurements. This visual representation provides valuable insights into the drone's surroundings and the accuracy of the distance measurements, enabling effective monitoring and analysis.

The presence of the crack is indicated as positive or negative in the dashboard of the web application as shown in Figure 3.

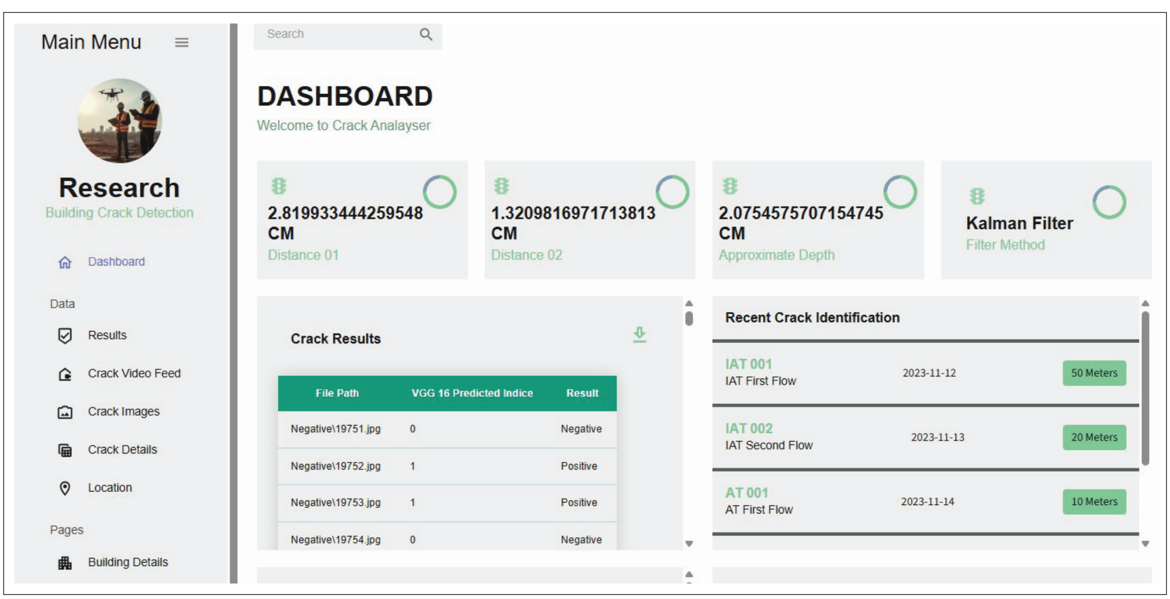
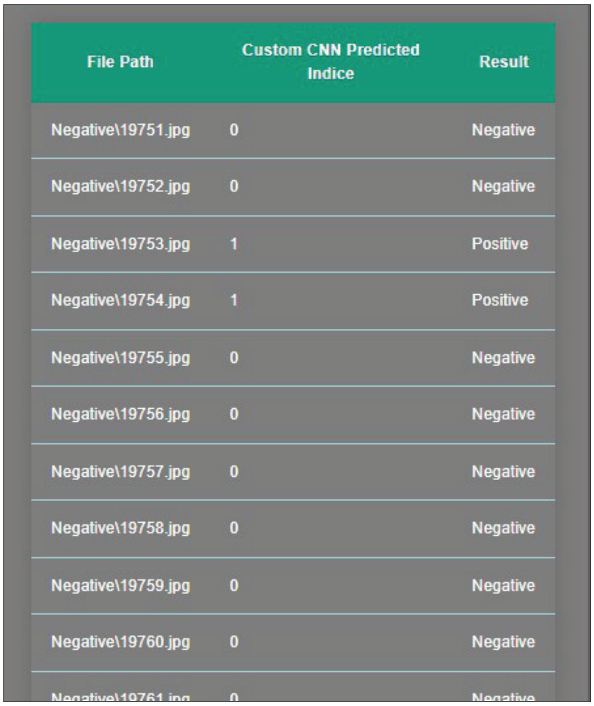


Figure 2: Interface of web application



File Path	Custom CNN Predicted Indice	Result
Negative\19751.jpg	0	Negative
Negative\19752.jpg	0	Negative
Negative\19753.jpg	1	Positive
Negative\19754.jpg	1	Positive
Negative\19755.jpg	0	Negative
Negative\19756.jpg	0	Negative
Negative\19757.jpg	0	Negative
Negative\19758.jpg	0	Negative
Negative\19759.jpg	0	Negative
Negative\19760.jpg	0	Negative
Negative\19761.jpg	0	Negative

Figure 3: Results of CCNN model on web application

Construction of deep learning models

In this study, both sonar and vision sensors were employed collaboratively to facilitate a comprehensive assessment of structural cracks in buildings. Ultrasonic waves emitted by sonar sensors are designed to penetrate into cracks, resulting in an increased measured distance between the UAV and the building surface—an indication of the presence of a crack. Upon such detection, the vision sensor (camera) is activated to capture an image of the affected area. This dual-sensing approach minimizes unnecessary image capture in areas without structural damage, thereby significantly reducing computational load and enhancing system efficiency.

This experiment was carried out with a dataset consisting of images collected from different surfaces of buildings with the available background light. The total dataset comprises 2,500 cracked and 2,500 non-cracked images as shown in Figure 5. This dataset is partitioned into training, validation, and testing subsets to support the development and evaluation of the model. Specifically, 2,000 images from each class (cracked and non-cracked) are allocated for training purposes. For validation, 250 cracked and 250 non-cracked images are used, while the testing set also consists of 250 images. This balanced distribution across all subsets ensures fair and unbiased performance assessment during model training and evaluation. A customized convolutional neural network (CCNN) model was implemented, with its architectural design illustrated in Figure 4. The proposed model was developed by systematically fine-tuning various hyperparameters within the network architecture to optimize performance.

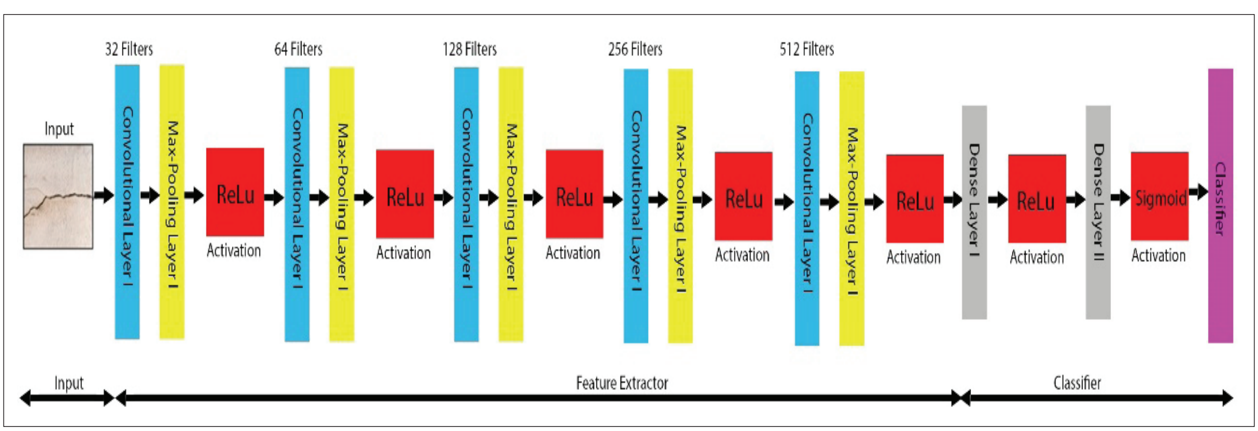


Figure 4: Architectural diagram of the proposed CCNN model

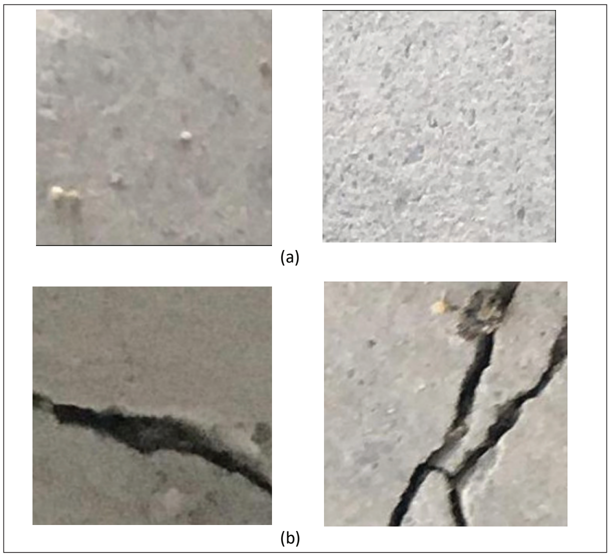


Figure 5: (a): Non-cracked images and (b) cracked images

Evaluation

Evaluation metrics such as precision, accuracy, F1-score, and confusion matrices have used in this research to assess the performance of the model.

Precision is an evaluation metric that measures the accuracy of positive predictions, indicating the model's ability to correctly identify true positives among all instances labelled as positive. Meanwhile, accuracy quantifies the overall correctness of the model's predictions across all classes or categories. The F1-score is a balanced measure of precision, and recall provides insight into the model's capability in handling imbalanced datasets.

Confusion matrices provide a comprehensive tabular representation of a model's predictions against actual values, delineating true positives, true negatives, false positives, and false negatives.

Model development and evaluation were conducted on a workstation with the following hardware and software configuration: RAM: 32 GB, CPU: Intel Core i7-11800H 2.30 GHz, and running a 64-bit Windows 11 operating system. The implementation was carried out using Anaconda JupyterLab 3.6.5 (Python 3.10), utilizing Keras 2.12 and TensorFlow 2.12 libraries.

RESULTS AND DISCUSSION

Drone performance results

This section showcases the evaluation of camera and image performance of the UAV developed for building crack detection. The drone's total payload, weighing 1405 g, includes a frame, flight controller with sensors, battery, enclosure, and propellers. This weight was carefully optimized to balance the drone's flight stability and power consumption.

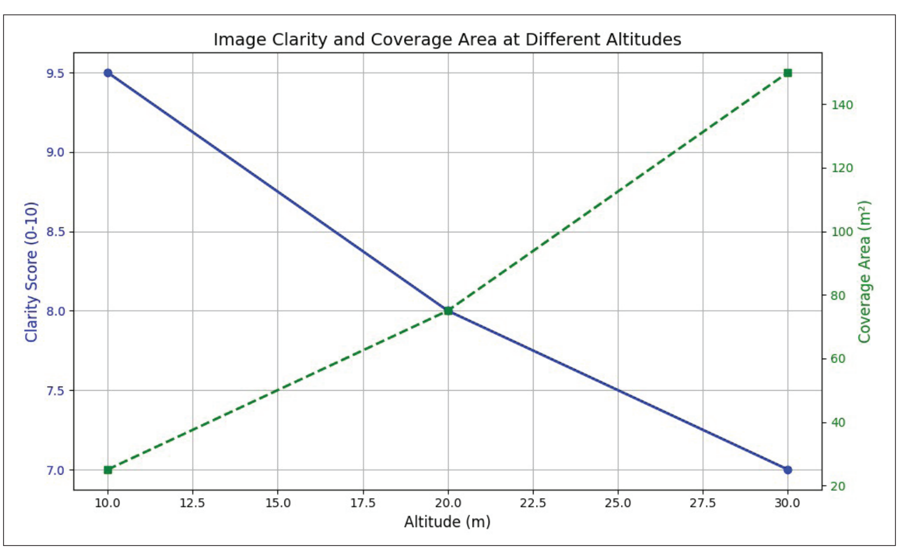


Figure 6: Image Clarity at Different Altitudes Data

Image clarity at different altitudes

The camera's image clarity and coverage area performance were evaluated at varying altitudes to determine the optimal flying height for crack detection. The image resolution remained constant at 2592 x 1944 pixels across all tested altitudes, but clarity and coverage area varied based on altitude.

Image clarity decreases as the altitude increases as shown in Table 1. At 10 meters, the camera provided the best clarity with a score of 9.5, which is ideal for detecting fine details of the cracks. At 20 meters, the clarity score drops to 8.0; at 30 meters, it decreases to 7.0. This may result in some loss of detail, potentially making it harder to detect smaller cracks. As expected, coverage area increases significantly with altitude: 25 m² at 10 meters, 75 m² at 20 meters, and 150 m² at 30 meters. Higher altitudes allow for covering larger areas in less time but at the reduction of image clarity. Image clarity and coverage area at different altitudes is shown at Figure 6.

Table 1: Image Clarity at Different Altitudes Data

Altitude (m)	Image Resolution (pixels)	Clarity Score (0-10)	Coverage Area (m²)
10	2592 x 1944	9.5	25
20	2592 x 1944	8.0	75
30	2592 x 1944	7.0	150

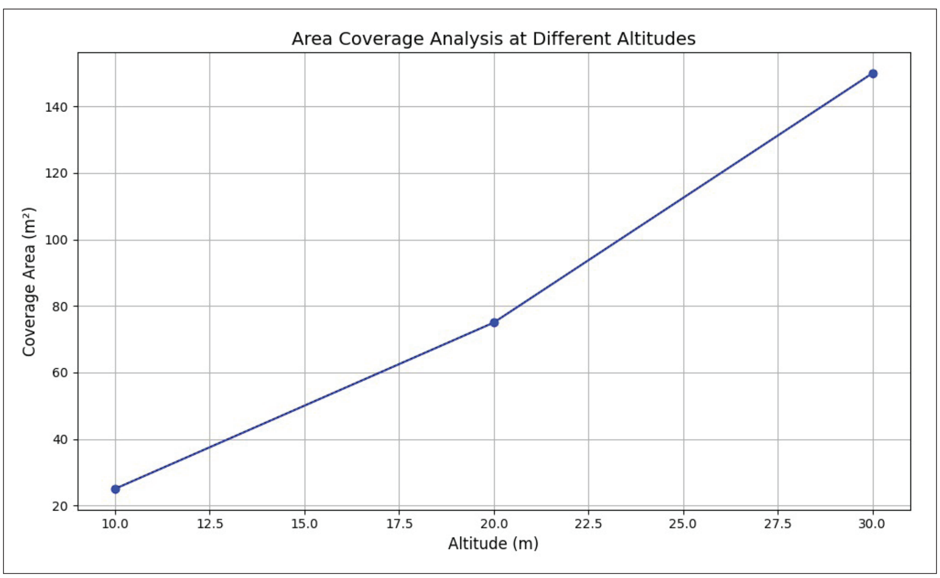


Figure 7: Line chart of area coverage at different altitudes

Area coverage analysis

The camera's field of view remained consistent across all altitudes, providing a 53° horizontal angle. However, the coverage area of each image increased with the altitude, as shown in the Table 2. Line chart representing the area coverage at different altitudes is shown in Figure7.

Table 2: Area coverage analysis data

Altitude (m)	Field of View (degrees)	Coverage Area (m²)
10	53	25
20	53	75
30	53	150

Results of deep learning models

CCNN achieves an accuracy of 99%, showcasing its effectiveness in overall classification performance. CCNN exhibits a precision of 98% and 98% indicating a low false-positive rate in their predictions. CCNN attains recall at 98%, highlighting its ability to effectively capture a significant portion of true positive instances. CCNN achieves an F1 score of 98%, emphasizing a harmonious balance between precision and recall.

The confusion matrices provide a detailed breakdown of the performance of customized CNN (Figure 8), consisting of two classes: the actual class (rows) and the predicted class (columns). True positives (TP) are 244; true negatives (TN), 246; false positives (FP), 4; and False Negatives (FN), 6. The model demonstrates exceptional performance with minimum false negatives, achieving a perfect balance between precision and recall.

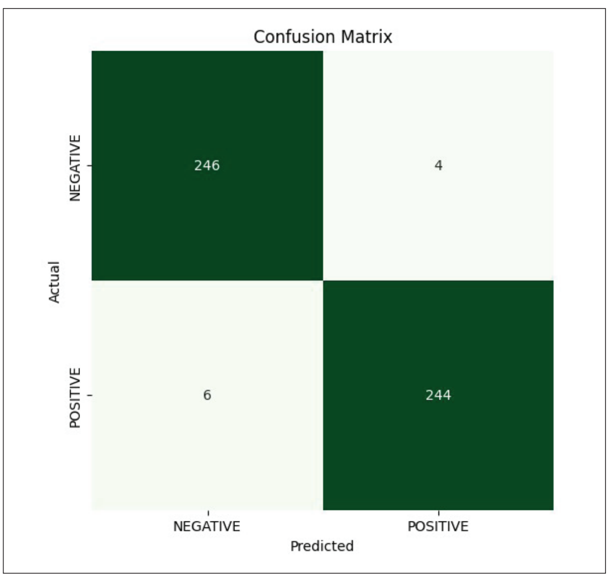


Figure 8: Confusion matrix of CCNN

The provided ROC curve and corresponding area under the curve (AUC) values offer a concise assessment of the classification performance for Customized CNN as shown in Figure 9. The ROC curve for customized CNN exhibits the highest performance, as reflected by the high AUC value of 0.99. This signifies that the model achieves an exceptional balance between true positive rate and false positive rate across various classification thresholds. The curve's proximity to the upper-left corner underscores the model's robust discriminative ability, indicating superior classification accuracy.

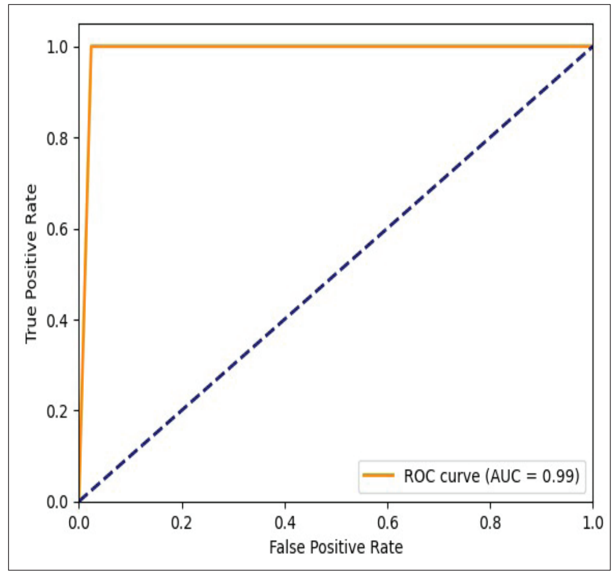


Figure 9: ROC curve of CCNN

CONCLUSION

In conclusion, this research embarks on an innovative exploration of an advanced approach to building crack detection. This research proposed an approach, leveraging both vision and non-visual sensors, to detect cracks through a comprehensive examination of the limitations in conventional image processing and the computational challenges of the deep learning model. The experiment, conducted with a UAV-mounted camera and sonar sensors, exemplifies the practical implementation of these methodologies. The customized deep CNN model underlines the significance of a tailored approach in achieving precision-driven building crack inspection. The resuts obtained from this research are compared with the state-of-art research (Ali *et al.*, 2021; Słoński, 2019; Fang *et al.*, 2020).The findings of this research contribute not only to the theoretical understanding of deep learning applications in infrastructure assessment but also provide practical insights for the deployment of UAVs for building crack detection.

To further improve this research, several enhancements can be considered. First, implementing a feature that automatically schedules maintenance tasks based on the detected cracks and their severity. Second, extending the system's capabilities to detect cracks in various types of structures beyond buildings, such as bridges and pavements, can broaden its applicability and utility. Further, it is expected to identify the features of the detected crack and classify them accordingly. The outlined deep learning techniques, experimental results, and model evaluations collectively contribute to the evolving landscape of accurate and efficient building crack detection.

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