Automated Building Exterior Wall Crack Inspection System Using UAVs and AI-Driven Image Analysis: A Case Study from Zambia

Alick NGUVULU, Penjani H. NYIMBILI, Happy MAKAYI, Balimu MWIYA and Erastus MWANAUMO, Zambia

Key words: UAV inspection, crack detection, convolutional neural networks, building maintenance, structural health monitoring, geomatics applications

SUMMARY

Building exterior inspections are critical for maintaining structural integrity and ensuring safety. Traditional manual inspection methods are labor-intensive, risky, and expensive, particularly for high-rise buildings. This paper presents the development and implementation of an Automated Building Exterior Wall Crack Inspection System (ABEWCIS) using a DJI Tello Unmanned Aerial Vehicle integrated with Convolutional Neural Networks for real-time crack detection. The developed ABEWCIS was tested on a dataset comprising high resolution images of cracks on exterior walls of buildings at the Copperbelt University, Zambia collected using smartphones and the DJI Tello UAV with a 14 minutes endurance. Additional images were downloaded from public databases to increase dataset diversity. To improve model discrimination, images of non-wall features like trees, cars, and furniture were also added to the dataset. The dataset was split into 80% training set and 20% validation set. To test its robustness, the ABEWCIS was run under different lighting, surface variation, and complex environmental conditions. The six-layer CNN model was compiled with the Adam optimizer and the binary crossentropy as the loss function. The model parameters were set to 30 epochs maximum with early stopping, batch size of 64 images per batch., and optimized using EarlyStopping and ReduceLROnPlateau callbacks. The ABEWCIS's performance in crack detection reached 85% true positive detection rates while reducing false positives to 10% demonstrating its employability and offering improvements in inspection accuracy, safety, and efficiency compared to traditional methods. Under the different conditions, the ABEWCIS's performance ranged from 80% to 95 % in true positive crack detection rates representing a substantial advancement over traditional manual inspection methods. The successful implementation of ABEWCIS in Zambia provides a model for similar developing countries to adopt advanced inspection technologies, potentially leading to improved infrastructure safety and longevity across the developing world. This study establishes a foundation for continued development in automated structural inspection systems, contributing to safer, more efficient, and more sustainable infrastructure management practices globally. Furthermore, the study contributes to the advancement of automated structural inspection technologies, particularly relevant for developing countries where cost-effective solutions are essential.

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1. INTRODUCTION

Structural health monitoring and building inspection have become increasingly critical as urban infrastructure ages and the demand for efficient maintenance strategies grows (Encardio, 2024; Sisgeo, 2025). Cracks, which may be horizontal, vertical, stair-step, diagonal, or settlement, in building exteriors serve as early indicators of potential structural problems (Ajagbe, 2018; Pandey et al., 2025), signaling issues that may compromise safety, integrity, and aesthetics. Traditionally, the inspection process has been carried out manually by human inspectors, who often have to access high and difficult-to-reach areas using ladders, ropes, or scaffolding (, 2014). These methods not only expose inspectors to significant risks but also result in inconsistent findings due to human error and the subjective nature of visual inspections (Khan et al., 2021). Furthermore, manual inspection methods lack consistency in digital data making it difficult to carry out long-term analysis (Dais et al., 2023). This makes it challenging to accurately monitor the progression of cracks and other structural issues over time, leading to delayed maintenance and repair actions, which can further compromise the building's integrity (Pandey et al., 2025).

In Zambia, like in many other least developed economies, crack inspections are rarely conducted, likely due to the high costs and significant risks associated with traditional inspection methods. These limitations hinder regular maintenance and the early detection of structural issues, potentially leading to more severe damage over time. Without frequent inspections, minor cracks can develop into more significant problems, threatening the safety of the structures and the people using them (Encardio, 2024).

Recent technological advancements have introduced more efficient and safer alternatives to traditional inspection methods. For example, unmanned aerial vehicles (UAVs), commonly known as drones, equipped with high-resolution cameras and various sensors, have emerged as a powerful tool for building inspections (Li et al., 2021; Zhang et al., 2023). These UAVs can capture detailed images and videos of building exteriors from multiple angles, including hard-to-reach areas, without putting human lives at risk (Khan et al., 2021; Chen et al., 2025). This capability makes UAVs highly suitable for inspecting high-rise buildings, bridges, and other large structures (Chen et al., 2022; Park et al., 2024).

In addition to UAV technology, the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques has significantly improved the accuracy and efficiency of crack detection (Özgenel & Gönenç Sorguç, 2018; Dais et al., 2023). AI algorithms, particularly those based on convolutional neural networks (CNNs), can process and analyze images captured by UAVs to detect cracks with high precision (Li et al., 2021; Gopalakrishnan et al., 2018). This approach not only enhances the accuracy of inspections but also allows for the continuous monitoring of buildings over time, providing valuable data for predicting and preventing potential structural failures (Zhang et al., 2023; Park et al., 2024).

This paper proposes an Automated Building Exterior Wall Crack Inspection System (ABEWCIS) using Unmanned Aerial Vehicles (UAVs) and AI-driven image analysis to address the limitations of traditional methods. This system will enable real-time crack detection, allowing for immediate identification of structural issues and the ability to save video footage for detailed analysis. By reducing the risks and costs associated with manual inspections and providing a scalable, automated solution, ABEWCIS seeks to enhance the efficiency and reliability of building maintenance. This approach promises to improve safety, reduce operational expenses, and facilitate more frequent inspections, ultimately contributing to the long-term building infrastructure sustainability in Zambia. This aligns with the global trend towards smart city model, more efficient infrastructure management solutions and supports the UN SGD No. 9 and 11.

2. STUDY AREA

The study was conducted at the Copperbelt University in Kitwe, Zambia. The Copperbelt University is the second largest public university in Zambia. It was formerly the Zambia Institute of Technology from 1973 until 1988 when it was declared a university by an Act of parliament of Zambia. Except for a few buildings constructed in the last two decades, most of the building infrastructure are those built in the 1970s. A number of these buildings, both old and new, have developed different types of interior and exterior wall cracks ranging from barely visible to very visible.

3. MATERIALS AND METHODS

3.1 Materials

The study used the DJI Tello drone with a high-definition video streaming capability and maximum flight time of 14 minutes. It had no GPS navigation, limited movement capabilities and no obstacle avoidance sensors. Software packages and libraries included TensorFlow (tensorflow) for loading the pre-trained deep learning model, OpenCV (cv2) for video processing, display, and saving frames with detected cracks, NumPy (numpy) for array manipulation and preprocessing the images and djitellopy for controlling the DJI Tello drone with Python.

Dataset: comprised high resolution images collected using smartphones and the DJI Tello drone. Additional images were downloaded from public databases to increase dataset diversity.

The dataset was split into training set (80%) and validation sets (20%). Images of non-wall features like trees, cars, and furniture were also included in the dataset to improve model discrimination.

3.2 Methods

3.2.1 System Architecture

The ABEWCIS integrates several key components: a DJI Tello UAV equipped with a high-resolution camera, a CNN-based crack detection model, real-time image processing capabilities, and automated flight control systems. The system architecture enables autonomous navigation around buildings while capturing and analyzing images for crack detection in real-time.

3.2.2 Software Environment Setup

The development environment utilized Python 3.10.4 for compatibility with TensorFlow 2.9.0, ensuring optimal performance of the machine learning components. Key libraries included TensorFlow and Keras for deep learning model development and training; OpenCV for image processing and video stream handling; DJITelloPy for drone control and communication; NumPy for numerical computations and array operations; and Matplotlib for data visualization and performance analysis. Visual Studio Code served as the integrated development environment, providing comprehensive support for Python development and debugging capabilities.

3.2.3 CNN Model Architecture, Training and Performance Monitoring

***Model Architecture Design*:** The crack detection model employed a sequential CNN architecture specifically optimized for binary image classification tasks. The network comprised six primary layers:

1) Input Layer Configuration: The input layer was configured to accept images with dimensions of 150 × 150 × 3, where the spatial dimensions (150 × 150 pixels) represent the standardized image size, and the depth dimension (3 channels) corresponds to RGB color images.
2) Convolutional Layers and Feature Extraction: The feature extraction component consists of multiple convolutional layers (Conv2D). The first convolutional layer utilized 32 filters with a 3×3 kernel size, applying the Rectified Linear Unit (ReLU) activation function. The subsequent convolutional layers systematically increased the number of filters to 64 and 128.
3) MaxPooling Layers (MaxPooling2D): Positioned after every convolutional layer to reduce the spatial dimensions of feature maps while retaining the most important information.
4) Feature Integration and Classification: This component comprised the Flatten Layer to convert the 2D output from the convolutional and pooling layers into a 1D vector

format; A fully connected layer (Dense Layer) containing 512 units with ReLU activation function; and a Dropout Layer with a rate of 0.5 implemented to prevent overfitting by randomly deactivating 50% of the units during training.
5) Output Layer: Consisted of a single unit with sigmoid activation function to produce an output value between 0 and 1. This configuration is optimal for binary classification tasks, where values closer to 0 indicate "no crack" and values closer to 1 indicate "crack present."

Model Compilation, Training and Optimization: The model was compiled with the Adam optimizer and the binary crossentropy as the loss function. Accuracy was the primary evaluation metric to track model performance during both training and validation phases. The parameters were set to maximum of 30 epochs with early stopping and a batch size of 64 images per batch. For optimization, two callbacks were implemented namely: EarlyStopping to monitor validation loss and ReduceLROnPlateau to reduce the learning rate when validation loss plateaus.

***Performance Monitoring and Visualization*:** Training progress was continuously monitored through tracking the training accuracy and loss for the training dataset and validation accuracy and loss detect overfitting early in the training process. Real-time visualization capabilities were implemented using Matplotlib to provide immediate insights into model performance trends. These visualizations included:

- Training and validation accuracy curves over epochs
- Training and validation loss progression
- Learning rate adjustments throughout training
- Performance comparison between training and validation sets

3.3 UAV Integration

The system integration process was done in the following steps: 1) Model loading: this involved deploying the pre-trained CNN model; 2) Frame preprocessing in which resizing and normalization of the image is done in real-time; 3) Prediction pipeline which involves automated crack detection on video stream; and 4) Flight control employing autonomous navigation patterns with crack detection pause functionality. The integrated system processes video frames in real-time, applying the trained CNN model to detect cracks. When cracks are detected, the system pauses flight operations for detailed inspection and documentation while overlaying detection results on the video stream.

4 RESULTS AND ANALYSIS

4.1 Model Performance Metrics

The ABEWCIS demonstrated significant performance improvements through iterative training and refinement. Table 1 shows the performance in terms of true positives, false positives, true negatives and false negatives.

Table 1 Model performance metrics in terms of true positives, false positives, true negatives and false negatives

Metric	Initial Performance	Improved Performance	Improvement
True Positives (Crack Detection)	60%	85%	+25%
False Positives	30%	10%	-20%
True Negatives (No Crack Detection)	55%	90%	+35%
False Negatives	25%	5%	-20%

4.2 Training Performance Analysis

The training process showed consistent improvement over epochs, with both accuracy and loss metrics indicating effective learning. The accuracy was 92% by epoch 25 for training, and 90% with minimal overfitting for validation. The loss decreased from 0.7 to 0.15 for training and reduced to 0.18 with stable convergence for validation. The learning curves (Fig. 2) demonstrated optimal convergence without significant overfitting, indicating good generalization capability.

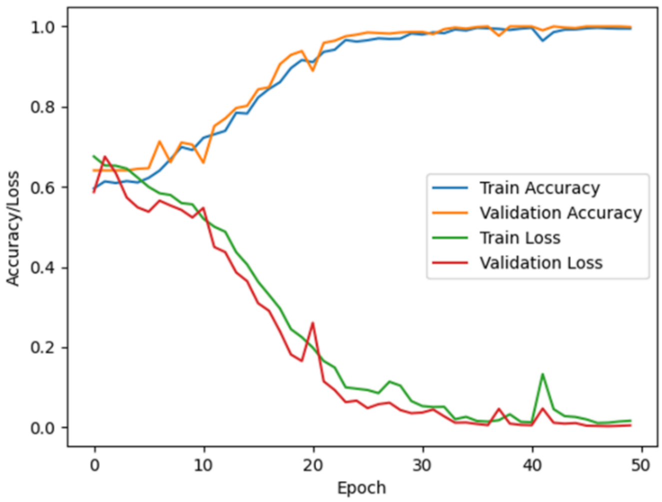

Fig. 2 Model learning curves showing the training accuracy and loss and the validation accuracy and loss used in analysing the model training performance

4.3 Environmental Testing Results

The ABEWCIS's robustness was tested under various conditions including lighting, surface variations, and complex environments and assessed using accuracy as shown in Table 2 .

Table 2 Conditions used to test the Automated Building Exterior Wall Crack Inspection System

Condition	Sub-condition	Accuracy (%)	Comment
Lighting	Daylight	88	Accuracy in optimal lighting
	Overcast	82	Accuracy with slight performance reduction
	Low light	75	Accuracy with increased preprocessing requirements
Surface Variation	Concrete surface	90	Accuracy (optimal performance)
	Painted surface	85	Accuracy with some false positives on texture patterns
	Weathered surface	80	Accuracy due to surface irregularities
Complex Environment	Vegetated	95	Correct non-crack classification
	Shadows	88	Correct classification with enhanced preprocessing
	Architectural features	92	Correct differentiation from structural cracks

4.4 Inspection Efficiency, Safety and Comparison with Traditional Methods

The inspection efficiency of the ABEWCIS was 200 square meters per 10-minute flight in terms of coverage, 30 frames per second with real-time analysis in terms of image capture and 0.3 seconds per frame processing time in terms of detection speed. The automated system eliminated direct human exposure to hazardous inspection environments by 100% elimination of height-related inspector risks, automating navigation thereby reducing human error factors and ensuring consistency. Further the system complete video recording for post-inspection analysis ensures digital documentation. The study further compared the efficiencies of the ABEWCIS with traditional methods and the findings are summarised in Table 3.

Table 3 Comparative Analysis with Traditional Methods

Aspect	Traditional Manual Inspection	ABEWCIS	Improvement Factor
Time required	2-4 hours per building section	15-30 minutes	4-8x faster
Safety risks	High (falls, equipment failure)	Minimal (UAV operation)	Significant reduction
Consistency	Variable (inspector dependent)	High (automated analysis)	Substantial improvement
Cost per inspection	$200-400	$50-100	2-4x cost reduction
Data documentation	Manual notes, limited photos	Complete video record, automated analysis	Comprehensive enhancement

5 DISCUSSION

5.1 Technological Implications

The successful development and implementation of ABEWCIS demonstrates the viability of integrating UAV technology with AI-driven analysis for structural inspection applications. The system's performance improvements, particularly the reduction in false positives from 30% to 10%, indicate that machine learning models can be effectively trained to distinguish between actual structural issues and environmental artifacts. The use of open-source software tools proves that cost-effective solutions can achieve performance levels comparable to proprietary systems. This finding is particularly significant for developing countries where budget constraints often limit access to advanced inspection technologies.

5.2 Practical Applications and Scalability

The ABEWCIS architecture demonstrates high adaptability for various inspection scenarios beyond building crack detection. Within infrastructure, these may include road surface monitoring, bridge inspections, and industrial facility monitoring. In agricultural applications, the system may be use for crop health monitoring and automated animal health and behavior analysis. This system's ability to capture, process, and analyze spatial data in real-time aligns with modern geomatics practices emphasizing automation and efficiency. The CNN-based approach to image analysis represents an advancement in automated spatial feature extraction, reducing reliance on manual interpretation while improving consistency and objectivity in spatial data analysis. The system's data output format enables seamless integration with Geographic Information Systems (GIS) for comprehensive spatial analysis and long-term monitoring. Detected crack locations can be georeferenced and incorporated into building information models (BIM) for enhanced facility management.

5.3 Economic Impact Analysis

In terms of cost-benefit analysis, the economic advantages of ABEWCIS extend beyond direct inspection cost savings. They include of preventive maintenance through early crack detection which reduces major structural repair costs; insurance benefits through regular automated inspections; and labor reallocation to focus on higher-value maintenance activities. Further, the open-source approach significantly improves market accessibility and reduces barriers to entry through elimination of licensing fees for proprietary solutions, simplified training protocols compared to complex manual inspection techniques and reduction in initial investment requirements for consumer-grade UAVs.

6. CONCLUSIONS

This research successfully demonstrates the development and implementation of an Automated Building Exterior Wall Crack Inspection System (ABEWCIS) using UAVs and AI-driven image analysis. The system achieved significant performance improvements, reaching 85% true positive detection rates while reducing false positives to 10%, representing a substantial advancement over traditional manual inspection methods. The successful implementation of

ABEWCIS in Zambia provides a model for similar developing countries to adopt advanced inspection technologies, potentially leading to improved infrastructure safety and longevity across the developing world. This research establishes a foundation for continued development in automated structural inspection systems, contributing to safer, more efficient, and more sustainable infrastructure management practices globally.

Key Contributions include:

- Technical Innovation: The integration of open-source software tools with UAV technology provides a cost-effective solution for automated structural inspection, making advanced technologies accessible to developing countries and resource-constrained organizations.
- Practical Impact: The system demonstrates measurable improvements in inspection efficiency, safety, and consistency while reducing operational costs and human risk exposure. The 4-8x improvement in inspection speed coupled with comprehensive documentation capabilities represents significant practical value.
- Geomatics Advancement: This work contributes to the evolution of geomatics engineering by demonstrating effective integration of remote sensing, artificial intelligence, and spatial analysis for infrastructure monitoring applications.
- Implications for Practice: The research provides a foundation for widespread adoption of automated inspection technologies in developing countries, addressing critical infrastructure monitoring needs with accessible, cost-effective solutions. The demonstrated success of open-source approaches challenges the assumption that advanced inspection capabilities require expensive proprietary systems.

6. RECOMMENDATIONS

Based on the experience during with and initial findings of this study, the following recommendations are made:

6.1 Technical Enhancements

6.1.1 Hardware Improvements

Future iterations should incorporate enhanced UAVs for longer flight times, GPS navigation, and obstacle avoidance capabilities; higher resolution sensors with better low-light performance; and onboard processing capabilities to reduce latency and improve real-time performance.

6.1.2 Model Sophistication

Algorithm should incorporate capabilities for:

- Multi-class classification to distinguish between different types of cracks and their severity levels

- 3D analysis capabilities for crack depth assessment
- Temporal analysis for crack progression monitoring through time-series analysis

6.2 Integration Opportunities

There exist opportunities for integrating the ABEWCIS with other systems like the Building Information Modeling (BIM) and the Smart Building Systems (SBS). Integration with BIM systems would enable linking detected cracks to specific building elements through spatial correlation, automated generation of maintenance recommendations for highly efficient maintenance scheduling, and long-term building health tracking and analysis through lifecycle management. Integration with SBS through connection with IoT infrastructure could provide continuous monitoring through integration with building sensor networks, predictive maintenance via machine learning-based failure prediction, and automated reporting through integration with facility management systems.

6.3 Deployment Strategies

6.3.1 Training and Capacity Building

Successful implementation requires technical training programs for local technicians and engineers, maintenance protocols and standard operating procedures for system operation, and quality assurance and validation procedures for detection accuracy.

6.3.2 Regulatory and Ethical Considerations

In terms of regulatory considerations, implementation must address aviation regulations existing in specific jurisdictions as to ensure UAV operation compliance. Secondly issues of data privacy i.e., handling of building imagery and sensitive information, must be addressed. Professional standards must also be upheld in accordance with existing inspection and certification processes.

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BIOGRAPHICAL NOTES

Dr. Alick Nguvulu
Dr. Alick Nguvulu is a Lecturer at the Department of Geomatic Engineering, School of Engineering, University of Zambia, Great East Road Campus, Lusaka, Zambia.

Happy Makayi
Mr. Happy Makayi is

Dr. Penjani Hopkins Nyimbili
Dr. Penjani Hopkins Nyimbili is a Lecturer at the Department of Geomatic Engineering, School of Engineering, University of Zambia, Great East Road Campus, Lusaka, Zambia.

Dr. Balimu Mwiya
Dr. Balimu Mwiya is a Lecturer at the Department of Civil and Environmental Engineering, School of Engineering, University of Zambia, Great East Campus, Lusaka, Zambia.

Prof. Erastus Mwanaumo
Prof. Erastus Mwanaumo is a Lecturer at the Department of Civil and Environmental Engineering, School of Engineering, University of Zambia, Great East Campus, Lusaka, Zambia.

CONTACTS

Dr. Alick Nguvulu
University of Zambia
School of Engineering
Lusaka
ZAMBIA
Tel. +260974574430
Email: alick.nguvulu@unza.ac.zm
Web site: www.unza.zm