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A Low-Cost UAV-Based Framework for Post-Seismic Crack Detection with CNN and Gesture Control

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***Abstract*— Traditional post–earthquake inspections are slow, costly, and subject to human error. This paper presents an autonomous structural inspection system that combines a low–cost unmanned aerial vehicle (UAV) with a Proportional–Derivative (PD) flight controller, a convolutional neural network (CNN) for crack detection, and a gesture–based user interface for intuitive operation. Implemented on a DJI Tello platform, the system achieves $98\,\%$ validation accuracy on a dataset of 15,594 images while maintaining stable flight and executing predefined inspection trajectories via hand gestures. Results indicate the feasibility of integrating UAVs and deep learning to optimize post–seismic inspection workflows.**

***Index Terms*— UAV, CNN, Structural inspection, Crack detection, Gesture control.**

I. Introduction

Mexico City is located in a highly seismic region, which increases the likelihood of structural damage in buildings. Manual post–earthquake inspections remain expensive, slow, and potentially subjective, motivating autonomous solutions that reduce cost and error while improving coverage and safety. Recent research has explored UAVs and computer vision for structural inspection [1]–[3]. Nevertheless, limitations persist in ease of use, robustness to environmental noise, and deployment with affordable platforms.

Recent research has further demonstrated the potential of UAVs for structural health monitoring. Early feasibility studies confirmed that airborne images captured by drones provide sufficient resolution and accuracy to support crack detection tasks, proving to be a viable alternative to conventional bridge-inspection vehicles [4]. Subsequent works focused on tower and concrete structures showed that drone-based image processing systems could detect cracks and rust in real time, significantly reducing inspection time compared to manual workflows. These contributions laid the foundation for integrating autonomous UAVs with computer vision to address structural safety concerns.

With the advancement of deep learning, convolutional neural networks (CNNs) have rapidly become the dominant approach for crack detection. Studies applying CNNs to high-rise buildings achieved accuracies exceeding 90%, highlighting their capability to automatically extract discriminative features without manual intervention. Lightweight models such as CrackScopeNet were also introduced to operate efficiently on resource-constrained drone platforms, ensuring practical deployment in real-world scenarios [5]. Similarly, transfer learning strategies using pretrained models like ResNet and MobileNet have been optimized for embedded devices such as Nvidia Jetson Nano, offering reliable real-time inference directly on board UAVs.

Beyond simple detection, several systems emphasize integrated and real-time functionalities. Recent works have combined UAVs with IoT frameworks and edge computing to transmit and analyze inspection data seamlessly. Other studies propose automatic trajectory control, where drones autonomously approach damage zones while concurrently classifying and measuring crack widths. For large-scale infrastructures such as levees and dams, both satellite and UAV imagery have been used to extend monitoring to disaster-prone areas [6]. These advances underscore the growing relevance of UAV-based AI systems not only in research but also in practical deployment for structural inspection.

This work contributes a practical system that integrates: (i) a PD controller for flight stabilization, (ii) a LeNet–based CNN for real–time crack detection, and (iii) a gesture–based control interface to eliminate the need for a handheld remote. The novelty lies in combining these components on an inexpensive commercial UAV, demonstrating reliable performance for post–seismic inspection scenarios.

II. Methodology

A. UAV Platform and Flight Control

A DJI Tello, Fig. 1, UAV was selected due to its affordability, compact size, and open programming interfaces, which make it particularly suitable for research and educational purposes. The platform provides an accessible entry point for developing and testing autonomous inspection algorithms while maintaining a balance between cost and functionality.

Fig. 1: DJI Tello drone (image credit: https://www.dji.com/).

In addition to technical considerations, regulatory factors played a significant role in the choice of UAV platform. In Mexico, aviation regulations classify drones according to their weight, where lightweight UAVs under 250 g face fewer restrictions than larger systems intended for commercial use. As a result, drones such as the DJI Tello can be operated in controlled environments without advanced certification or permits. This lighter weight class enables operation for research and educational purposes while maintaining compliance with national legislation. Consequently, the choice of the DJI Tello platform facilitated the safe development and testing of autonomous inspection algorithms, providing a practical balance between legal feasibility, operational flexibility, and affordability.

Although the drone provides open programming interfaces, only its outer control loop can be accessed. This loop accepts velocity commands along the x, y, and z axes for linear displacements, as well as angular velocity commands for yaw rotation. To ensure stable altitude during flight, a proportional–derivative (PD) controller was implemented, allowing the UAV to maintain a consistent vertical position while executing inspection maneuvers.

The tuning of the PD controller was carried out heuristically, considering the trade-off between response overshoot and settling time. As illustrated in Fig. 2, the final tuned controller achieved a satisfactory balance that ensured stable altitude regulation during flight tests.

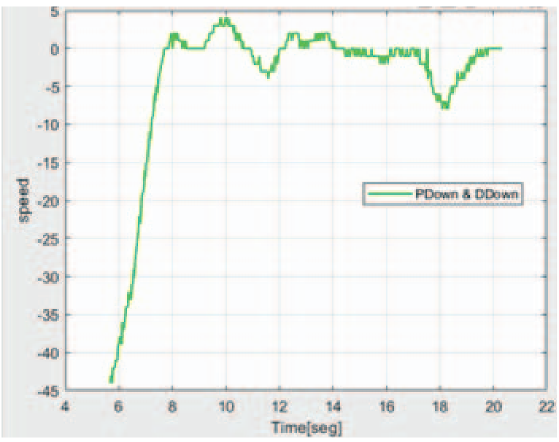


Fig. 2: Heuristically tuned PD controller used for altitude regulation.

B. Convolutional Neural Network

We adopt an adapted LeNet architecture with two convolutional layers, max–pooling, and three fully–connected layers. Input RGB images are resized to 28×28. Training uses TensorFlow/Keras for 100 epochs on 15,594 labeled images (7,168 crack, 8,426 non–crack), with a 25% validation split. The final model achieved 98% validation accuracy with 6% validation loss.

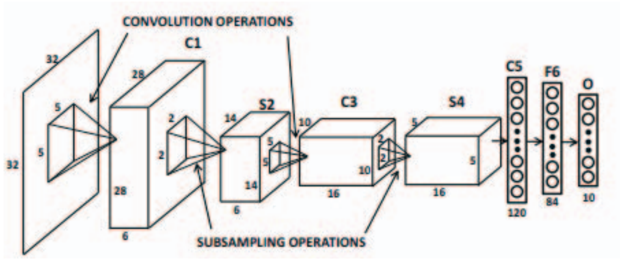


Fig. 3: LeNet-based CNN architecture used for crack detection.

In addition to the LeNet architecture employed in this study, alternative approaches have been proposed in the literature. For instance, transfer learning using pretrained models such as ResNet and MobileNet has been successfully deployed on embedded platforms like Nvidia Jetson Nano, enabling efficient inference directly on board UAVs [7]. Other works have explored integrating UAV inspection into IoT frameworks, where edge devices process captured images before transmission to centralized servers [8]. These studies highlight different strategies to balance model complexity and deployment constraints, but in our case, a lightweight CNN was preferred to ensure compatibility with the low-cost DJI Tello platform without requiring specialized hardware.

The training dataset consisted of 15,594 labeled images of concrete surfaces, collected from both public crack image repositories [9], [10] and original UAV captures at the Tecnológico de Monterrey campus. The dataset was balanced between crack and non-crack samples to prevent bias, and images were resized to 28×28 RGB format before training. A 75/25 split was applied for training and validation, ensuring that the CNN was tested on previously unseen samples. Data augmentation techniques, including rotation and brightness adjustment, were also applied to improve robustness against variations in lighting and perspective. Representative examples of crack and non-crack samples used in the dataset are shown in Fig. 4.

Fig. 4: Representative samples from the dataset used for training, including crack and non-crack images.

C. Gesture–Based Control

Gesture commands are implemented using CVZone [1] over Mediapipe. Six gestures (*up, down, left, right, forward, start*) map to altitude/translation increments and to the execution of a predefined inspection path. The UAV maintains a safe standoff distance from the operator and reorients toward the facade before executing a vertical sweep.

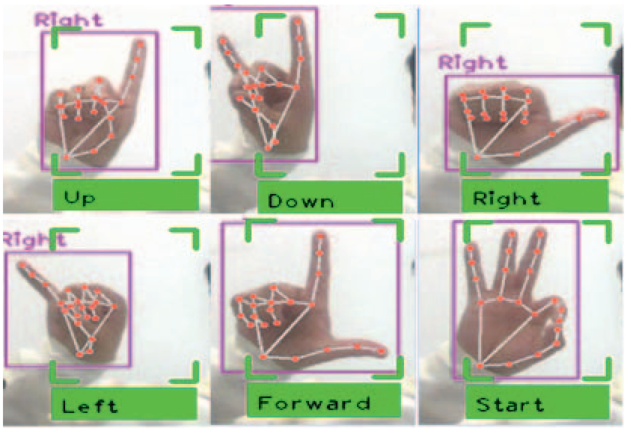


Fig. 5: Defined hand gestures (up, down, left, right, forward, start) and their UAV command mapping.

This gesture-based interface proved to be intuitive and reliable, allowing operators with no prior piloting experience to command the UAV effectively. The integration of gesture control enhances usability and safety by reducing dependence on traditional remote controllers and enabling hands-free interaction during inspection tasks.

D. Overall System

The complete inspection system integrates the UAV platform, the PD controller for flight stabilization, the CNN for crack detection, and the gesture-based interface for human interaction. As illustrated in Fig. 6, the workflow involves a human operator issuing gesture commands, the UAV responding with stable movements, and the onboard CNN performing real-time crack identification.

III. Results

The proposed CNN achieved a validation accuracy of 98% with low false-positive and false-negative rates. Its performance remained robust across both static images and video sequences, although a slight degradation was observed under motion blur or when the background exhibited high texture complexity. The training and validation curves are shown in Fig. 7, where convergence was reached after approximately 80 epochs.

[1]https://github.com/cvzone/cvzone

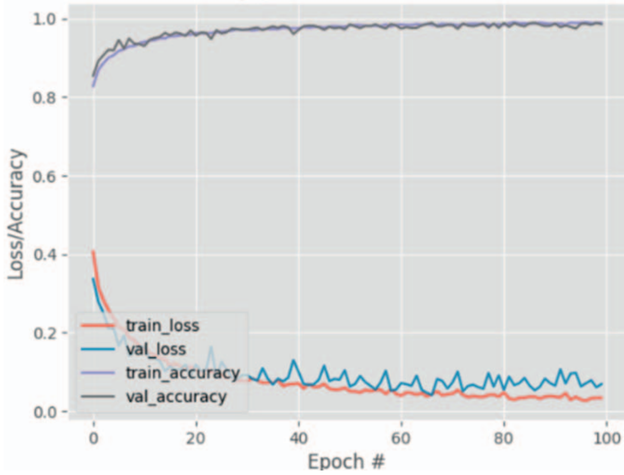


Fig. 7: Training and validation accuracy and loss over 100 epochs.

The PD controller ensured stable altitude regulation and reduced oscillations in response to perturbations. After gain tuning, the system achieved reduced overshoot and shorter settling times, which allowed dependable hovering for both data acquisition and gesture-based operation.

Field tests conducted at the Tecnológico de Monterrey (Santa Fe campus) confirmed the feasibility of the system for real-world crack inspection. Figure 8 presents representative examples of detection results obtained during UAV inspections. Subfigures (a) and (b), show successful identification of cracks in building facades with high confidence scores, while subfigure (c), illustrates a crack detected with a probability of 59.7%, highlighting the challenge of faint or low-contrast damage. Subfigure (d), demonstrates a scenario without cracks, where the CNN correctly classified the surface as intact. These outcomes validate the applicability of the proposed UAV-based approach, while also emphasizing limitations under conditions of low illumination, wind disturbance, and restricted battery autonomy.

IV. Discussion

The proposed integration of UAVs with deep learning and intuitive interaction demonstrates practical viability for post–seismic inspections. Compared with manual workflows, the approach reduces operator burden and accelerates coverage while maintaining high detection accuracy. Remaining challenges concern illumination variability, environmental disturbances, and platform endurance. Future prototypes should incorporate longer–endurance UAVs and additional sensing (e.g., thermal or depth) to enable reliable indoor operation and night/low–light scenarios.

Our validation accuracy of 98% compares favorably with previous UAV-based crack detection studies. For example, CNN-based approaches applied to high-rise buildings achieved accuracies around 90.7% with validation accuracy close to 89.8% [11], while deep learning methods on large datasets of concrete cracks reported F1-scores above 99% [12]. Similarly, real-time inspection systems leveraging YOLOv3 on embedded GPUs have reached accuracies in the

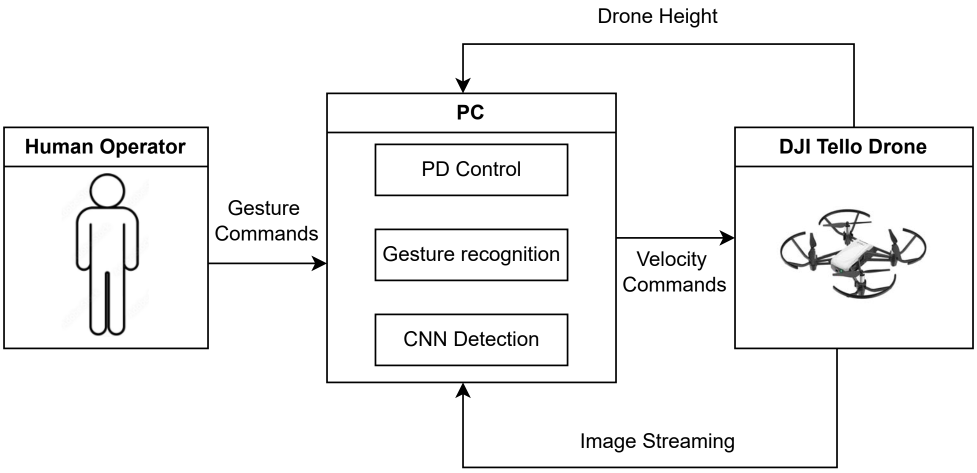
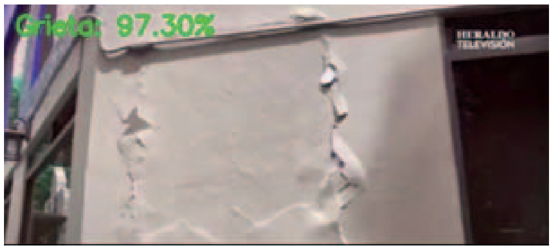


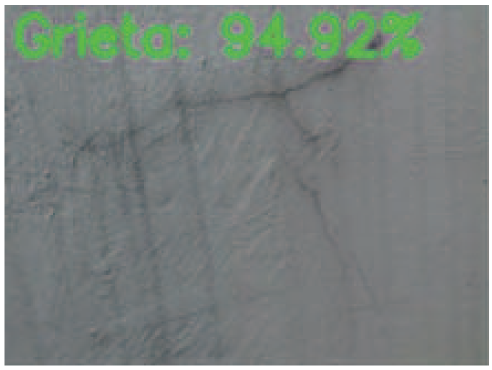
Fig. 6: Overall system schematic illustrating the interaction between the human operator, PC modules (Gesture Recognition, PD Control, CNN), and the UAV DJI Tello.

(a) Successful detection with high confidence.



(b) Detection of crack patterns on facade.

(c) Crack detected with 59.7% probability.



(d) Correct classification of a surface without cracks.

Fig. 8: Representative crack detection results during UAV field evaluation.

94% range for high-rise structures [13]. These comparisons confirm that our simpler architecture can match or even surpass more complex models in controlled scenarios.

Beyond buildings, UAV-based crack detection has also been applied to other infrastructure domains, including levee monitoring and road pavement inspection [14], [15]. While these applications demonstrate the versatility of UAVs and AI methods across contexts, our work focuses specifically on post-seismic building inspection, where rapid deployment and operational simplicity are essential. Nevertheless, lessons learned from such cross-domain studies suggest that further improvements in robustness to lighting, wind, and environmental conditions are possible through model optimization and sensor fusion.

V. Conclusion

This paper presented a low–cost UAV system for autonomous crack inspection that combines PD stabilization, a LeNet–based CNN, and gesture control. Experiments indicate strong detection accuracy (98%) and reliable autonomous behaviors suitable for post–earthquake inspections. Future work will focus on a graphical user interface, improved robustness in challenging environments, and evaluation on more capable UAV platforms compliant with national regulations.

Future work could also benefit from integrating UAV inspection into IoT and cloud-based frameworks, enabling real-time data streaming and advanced asset management, as demonstrated in SEMAR wall inspection systems [8]. Additionally, recent studies have extended crack detection to critical domains such as nuclear infrastructure [16] and port quay walls [17], showing the potential for broader adoption. Incorporating these perspectives may expand the applicability of our system beyond post-seismic building inspection, supporting a wide range of structural health monitoring tasks.

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