REAL-TIME DAMAGE DIAGNOSIS USING DIGITAL IMAGE CORRELATION METHOD AND DEEP LEARNING

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Abstract - Real-time crack detection is vital for structural health monitoring in high-safety systems. This study integrates a Digital Image Correlation (DIC) system with a lightweight Convolutional Neural Network (CNN) for automated damage diagnosis. The DIC system enables high-resolution full-field strain measurement under dynamic loading, and over 1500 annotated DIC images were used to train the CNN. The model achieved 81.9% precision, 83.4% recall, and 82.1% F1-score in detecting crack initiation and propagation. Compared to traditional DIC post-processing, the proposed method provides automated, accurate, and early detection while maintaining real-time performance. The system runs efficiently on standard computing hardware without GPU acceleration, demonstrating its robustness and feasibility for industrial applications. Experimental validation on metallic specimens confirmed the method's reliability and practical applicability in structural health monitoring.

Key words - Fault Diagnosis; Digital Image Correlation (DIC); Deep Neural Networks (DNN); Real-time Deformation.

1. Introduction

The detection and prediction of damage evolution in engineering components, such as cracking, residual deformation, or degradation of mechanical properties, play a crucial role in maintenance, operation, and the evaluation of structural remaining life. This is particularly vital in high-reliability sectors such as aerospace, electronics, biomedical engineering, and modern industrial manufacturing, where early fault diagnosis can help minimize risks, enhance operational efficiency, and reduce maintenance costs [1].

In practice, measuring deformation or displacement in components presents significant challenges, especially for structures at micro/nano scale, with non-uniform surfaces, or operating in harsh environments. Traditional measurement methods such as contact extensometers or strain gauges are limited in their spatial coverage, may interfere with the specimen, and do not allow for full-field surface strain monitoring.

To overcome these limitations, the Digital Image Correlation (DIC) method was developed in the 1980s by Sutton and colleagues at the University of South Carolina. DIC is a non-contact, non-destructive optical measurement technique that utilizes sequential digital images captured during the deformation process to determine surface displacement and strain fields through correlation algorithms [2]. Due to its significant advantages-non-contact nature, full-field measurement capability, ease of experimental deployment, and applicability to various materials including soft or delicate ones such as polymers, biomaterials, or shape memory alloys-DIC has become a powerful tool in experimental mechanics [3].

Typical applications of DIC include:

• Identifying complex strain fields in the vicinity of crack tips;

• Measuring mechanical properties such as Young's modulus, Poisson's ratio, and stress intensity factors [4];

• Monitoring crack initiation and propagation and fatigue behavior during operation [5];

• Applications in static, dynamic, thermal, or complex environmental testing (e.g., high temperature, corrosion, vibration) [6].

However, processing and analyzing DIC data, especially for complex geometries or continuous monitoring, can generate a large volume of strain field data. Effectively leveraging this data for fault detection and prediction requires support from intelligent data analysis techniques.

In this context, Artificial Intelligence (AI), particularly Deep Learning (DL), offers a promising approach to structural damage diagnosis and monitoring. Deep neural networks, such as Convolutional Neural Networks (CNNs), have demonstrated outstanding performance in image processing, feature extraction, and classification of highly complex datasets.

Compared to traditional DIC post-processing that often relies on thresholding or manual interpretation of strain fields, CNNs can automatically learn spatial features and detect cracks - even at early stages when deformation is minimal. Deep learning models, when integrated with DIC, can leverage experimental data to enhance both the accuracy and real-time responsiveness of monitoring systems [7], [8]. This significantly reduces operator dependence and enhances detection accuracy and repeatability, particularly in industrial environments where real-time assessment is critical.

Recent studies have demonstrated the feasibility of integrating DIC with deep learning for structural damage detection. For example, Zhang et al. [9] developed a system combining DIC and CNNs for early crack detection in composite materials. Another study by Yang et al. [10] employed Generative Adversarial Networks (GANs) to reconstruct strain field images and identify hidden cracks not visible to the naked eye.

Building on these advances, the present work develops a lightweight CNN model trained on over 1500 DIC images from mechanical tests of InnoLot solder joints. The system is capable of real-time inference on standard hardware without the need for GPU acceleration, making it practical for real-world deployment. Moreover, the model achieves classification metrics of 81.9% precision, 83.4% recall, and 82.1% F1-score, demonstrating reliable performance in automated crack detection.

By integrating high-resolution DIC with deep learning, this research addresses the limitations of conventional strain-based analysis and contributes toward the development of intelligent, real-time structural health monitoring solutions.

2. Method

2.1. Digital Image Correlation (DIC) Method

The Digital Image Correlation (DIC) method refers to an optical and non-contact measurement technique that involves the acquisition, storage, and correlation of digital images, a technique developed since the 1980s. It enables the generation of full-field strain maps on the surface of a specimen in all directions. DIC has evolved into a high-sensitivity technique for in-situ mechanical testing.

Two-dimensional (2D) in-plane DIC is based on the concept of a camera tracking features on the specimen surface. The camera sensor focuses on the planar surface of the specimen to capture images under different loading conditions. The specimen surface is typically painted or sprayed with black and white speckle patterns, assigning each pixel a grayscale value ranging from 0 (black) to 255 (white). Lighting is crucial to illuminate the black and white features on the surface. Additionally, the fundamental computation unit is a subset, consisting of several pixels. By grouping multiple pixels into a subset, DIC can correlate and detect the shape and displacement of each subset. Shear strain can be quantified by comparing the shapes of the subsets before and after deformation. The 2D DIC technique achieves a displacement measurement accuracy of 0.02 pixels.

The DIC technique works by comparing deformed images of the specimen surface with a reference image captured before deformation. The correlation algorithm requires the surface images to have a sufficiently fine speckle pattern, typically produced using an airbrush. In this study, the speckle pattern was created using a spray nozzle with a 0.2 mm diameter. This nozzle was adjusted to generate fine speckles on the surface, producing a random and smooth pattern with dot sizes in the millimeter range.

The reference image is divided into subsets with positions defined on the deformed images. Consider a subset cantered at point $P(x_0, y_0)$ in the reference image (see Figure 1). A point $Q(x_i, y_i)$ within this subset becomes point $Q'(x_i', y_i')$ after deformation in the target subset through the following transformation:

$$\begin{aligned} x_i' &= x_i + u + \frac{\partial u}{\partial x}\Delta x + \frac{\partial u}{\partial y}\Delta y \\ y_i' &= y_i + v + \frac{\partial v}{\partial x}\Delta x + \frac{\partial v}{\partial y}\Delta y \end{aligned} \tag{1}$$

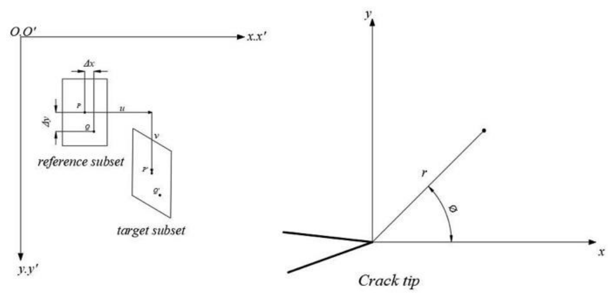
Where:

- u and v: are the displacement components of the reference subset at point $P(x_0,y_0)$.

- $\partial u/\partial x, \partial u/\partial y, \partial v/\partial x, \partial v/\partial y$: are the displacement gradients.

- $\Delta x = x_i - x_0,\ \ \Delta y = y_i - y_0$.

To estimate the similarity between the reference subset and the deformed subset, a correlation coefficient is calculated based on a specific criterion using the set of points within the subset. By searching for the extremum of this coefficient, the displacement of point P can be determined.



(a) (b)

***Figure 1.** (a) DIC method, (b) Polar reference related to the crack tip*

2.2. DIC system

2.2.1. Imaging Equipment

The DIC system is built around a GENIE series monochrome digital camera (model Genie 1400), which utilizes Gigabit Ethernet technology for communication with the host computer and is configured using the CamExpert software. The camera is equipped with a 1/2-inch CCD sensor (6.4 × 4.8 mm) offering a resolution of 1360 × 1024 pixels and a maximum frame rate of 15 frames per second. During image acquisition, the image format is set to 8-bit grayscale and saved in uncompressed ".tif" format to ensure high accuracy for the DIC algorithm. Table 1 presents the main specifications of the CCD camera used in this study.

***Table 1.** Main specifications of the CCD camera*

Parameter	Specification
Resolution	1360 × 1024 pixels
Pixel size	4.65 µm × 4.65 µm
Pixel format	8-bit, 10-bit
Imaging frequency	0.1 fps – 15 fps
Exposure time	100 µs – max. dependent on current frame rate

The camera is paired with a 10× macro zoom lens (Computar MLH-10X) with a C-mount. This lens allows for manual focal length adjustment from 13 mm to 130 mm, along with an aperture adjustment (f/5.6 maximum). This feature helps control the amount of light passing through the lens, directly affecting the depth of field and contrast, which are critical factors to ensure accuracy for the DIC algorithm.

Due to the small size of the specimen, the field of view (FOV) had to be reduced by placing the lens as close as possible to the sample while maximizing the magnification at this working distance. The lens has a minimum focusing distance of 152.4 mm and a maximum magnification of 0.84. As a result, the smallest achievable field of view is approximately 7.8 mm in width and 5.9 mm in height, with a pixel size at the object of 5.7 µm/pixel.

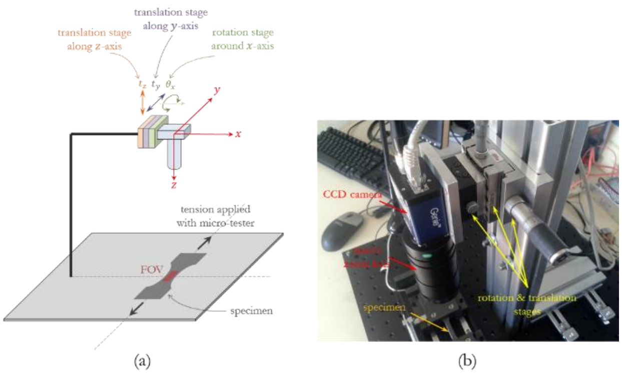


Figure 2. *Schematics of the DIC system (a) and the actual system (b)*

2.2.2. Lighting system

To ensure image quality, the lighting system is carefully considered. LED lighting is used because it provides uniform (diffuse) light, high intensity, and minimizes heat generation, thereby reducing any unwanted thermal effects on the specimen. Given the small size of the specimen, a simple LED light with an adjustable arm is sufficient to illuminate the area to be observed.

The entire imaging setup is mounted perpendicular to the specimen surface using a fixed support arm attached to a base with alignment holes, making it easier to position the experimental components. To fine-tune the position and angle of the camera relative to the specimen, a system consisting of two sliding tables and a rotating platform is used. This setup ensures precise alignment of the CCD sensor plane parallel to the specimen surface, minimizing errors caused by motion outside the plane.

2.2.3. Speckling

The accuracy of DIC significantly depends on the image contrast, particularly the quality of the speckle pattern. In this study, since the specimen has a natural surface with isotropic texture and appropriate density, it can be used directly. However, for comparison, a sample is coated with an artificial speckle pattern using matte (non-glossy) black and white paint to reduce light reflection. The speckle patterning process is performed using a spray gun with a fine nozzle (0.2 mm) and an air compressor regulated at 2 bar. The specimen is first coated with a white base layer, and then a light spray of black paint is applied to create a random pattern with spatial intensity variations.

Figure 3. *The speckling system*

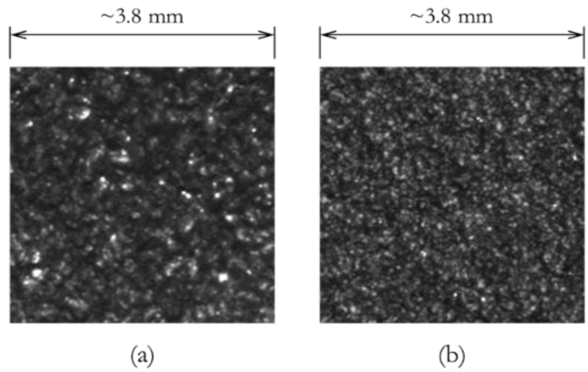


Figure 4. *Image (a) before speckling and (b) after speckling*

2.2.4. Evaluation of Optical System Performance

First, the noise level of the camera sensor is assessed by capturing two consecutive static images and calculating the grayscale difference at each pixel. Noise is defined as the ratio of the standard deviation of the grayscale difference distribution to the dynamic range (256 for 8-bit images). The measured noise value is approximately 0.87% of the dynamic range, indicating that the noise effect on DIC results is negligible.

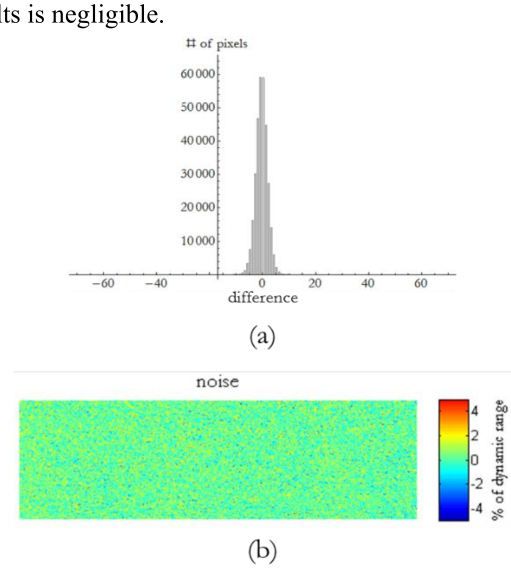


Figure 5. *DIC system evaluation*

Next, the displacement resolution of the system is determined by performing an autocorrelation test between two static images. The result yields a resolution of approximately 0.015 pixel (equivalent to 1/67 pixel). With a pixel size at the object of 15.45µm, the achieved displacement resolution is around 0.23 μm. This value is sufficient to obtain accurate DIC results in experiments with small specimens.

The developed DIC system ensures the precise measurement of strain and displacement fields on the surface, facilitating damage monitoring and mechanical analysis in micro details, especially when combined with deep learning models for automatic detection, diagnosis, and prediction of crack development.

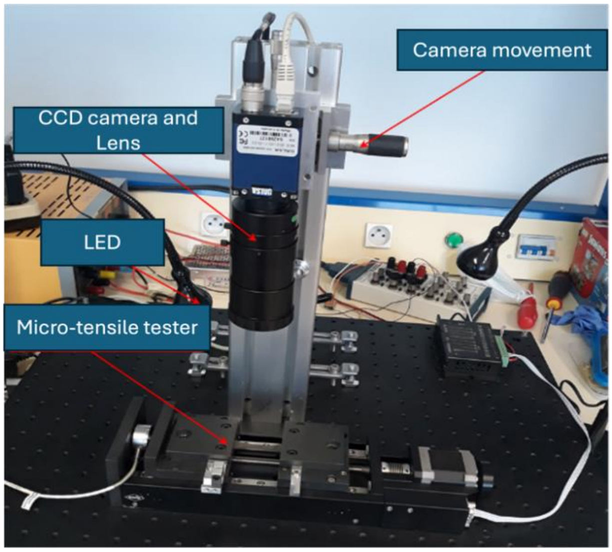


Figure 6. *Components of the DIC system after fabrication and installation*

2.3. Application of Deep Learning in DIC

In recent years, artificial intelligence (AI), particularly deep learning, has demonstrated exceptional potential in processing, analyzing, and extracting information from digital image data obtained from DIC systems. Integrating DIC with AI models opens up new approaches for monitoring damage, automating diagnostic processes, and predicting crack growth in micro-mechanical components. Convolutional neural networks (CNNs) are capable of pattern recognition, detecting anomalies, or identifying small changes in strain fields with high sensitivity.

When trained with deformation datasets from DIC images, these models can learn the geometric and dynamic features related to damage progression. Additionally, deep learning models have the ability to classify high-risk areas on the surface of components, aiding decision-making in predictive maintenance. Recent studies have used U-Net or ResNet models to reconstruct strain fields, locate cracks, and predict failure behavior over time. For example, Feng et al. [11] used U-Net to detect and segment cracks from DIC images with high accuracy, while Zhang et al. [9] implemented ResNet to estimate stress states in composite materials. Moreover, deep regression models have been deployed to estimate crack size, propagation direction, and growth rate, thereby building predictive models for component lifespan under complex loading conditions. These systems can be trained using large datasets from DIC images collected over multiple loading cycles.

In this study, a lightweight CNN architecture was implemented for real-time crack detection based on grayscale DIC images. The model consists of four 2D convolutional layers interleaved with max-pooling, followed by two fully connected layers and a softmax output for binary classification (crack/no crack).

Input images were resized to 128×128 pixels, cropped from the original DIC images, and manually annotated based on high-strain regions observed in the experimental strain fields. The dataset includes over 1500 labeled DIC images obtained from static tensile tests of InnoLot solder joints. 70% of the images were used for training and 30% for validation.

The model was trained using the Adam optimizer with a learning rate of 1e-4, batch size of 32, and binary cross-entropy loss over 50 epochs. Training and inference were performed in MATLAB on a standard CPU without GPU acceleration. This design enables fast processing and inference, making it suitable for integration into industrial monitoring systems that require continuous, real-time analysis.

Quantitatively, the trained CNN achieved a precision of 81.9%, recall of 83.4%, and F1-score of 82.1%, validating its capability in automated crack recognition. Compared to traditional machine learning methods such as SVMs, Random Forests, or MLPs, CNNs offer superior performance on DIC images due to their ability to extract complex spatial features without manual feature engineering. The integration of deep learning into the DIC framework thus significantly enhances its automation, sensitivity to early-stage damage, and adaptability across different materials and testing scenarios.

2.4. Materials and Experimental Procedure

In this study, the lead-free solder material InnoLot was selected for investigation. The chemical composition of this material is presented in Table 2. Further examination of InnoLot was carried out to better understand its properties and to explore potential improvements for optimal performance under the harsh operating conditions found in automotive applications.

Table 2. *Chemical composition of InnoLot solder material.*

Sn	Ag	Cu	Sb	Bi	Fe	Al	As	Ni	T_c	T_n
90.8	3.8	0.7	1.54	3.0	0.003	<0.001	0.005	0.15	218^{0}C	206^{0}C

To accurately predict the crack propagation path, the experimental specimen must have dimensions equivalent to those of actual components. Soldered parts used in automotive applications are typically very small, ranging from several hundred micrometers to a few millimeters. Therefore, the specimens were fabricated with a maximum dimension in the millimeter range. The fabrication process was carried out according to the following steps:

Step 1: The solder material was first melted in a furnace at a temperature at least 100°C above its melting point, using a graphite crucible;

Step 2: Once the solder was fully molten, it was rapidly poured into a metal mold made of 304-grade stainless steel, with dimensions of 80 × 18 × 16 mm. The mold was placed in water maintained at a temperature of 25–35°C to ensure the required cooling rate;

***Step 3**:* After approximately 3–5 minutes, the solidified casting was easily removed from the mold;

***Step 4**:* The casting was then cut into small and thin specimens using wire EDM. The final specimen dimensions were 20 × 6 × 1 mm, with a corner fillet radius of 17 mm to reduce stress concentration;

***Step 5**:* Finally, before testing, the specimens were stress-relieved by annealing at 100°C for 2 hours, followed by air cooling in a static atmosphere to eliminate residual stresses from the EDM process.

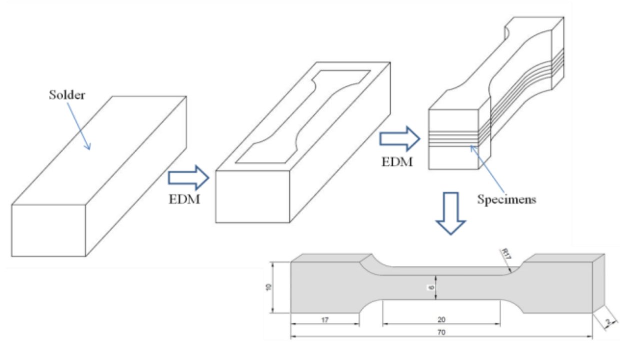


***Figure 7.** Fabrication process of the experimental specimen*

During tensile testing, high-resolution grayscale images of the specimen surface were captured using the DIC system at a frequency of 1 frame per second. These images were saved in uncompressed format and served as the primary data source for training the CNN model.

The speckle pattern on the specimen ensured sufficient contrast for deformation tracking, and the camera setup enabled a pixel resolution of 5.7 µm/pixel.

From these tests, over 1500 annotated DIC images were extracted for crack detection model development, focusing on the onset and propagation of damage under static loading.

3. Results and Discussion

After the experimental setup was completed, the specimen was tested at a tensile speed of 2.0×10^{-4} mm/s. A CCD camera was configured to capture one image per second, and the images were stored on a computer for further analysis. These images were subsequently extracted and processed by a custom computational program.

Figure 8 illustrates the image analysis process using Digital Image Correlation (DIC) technology in combination with Artificial Intelligence (AI), specifically a Convolutional Neural Network (CNN) model, to segment and predict crack propagation in the material. The process begins with acquiring digital images from the DIC system. These images are then fed into the AI model, where features such as deformation patterns and surface texture of the specimen are analyzed. The CNN model learns to recognize key characteristics in the DIC images to segment cracks and determine their location, size, and propagation direction over time.

The final analysis results are presented as simulated images or crack maps, enabling assessment of material durability and crack growth prediction under various loading conditions. This process not only improves accuracy but also enhances analysis efficiency, particularly in experiments involving small specimens or when large volumes of image data need to be processed quickly.

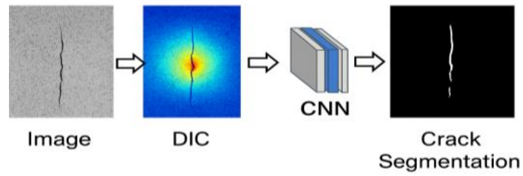


***Figure 8.** Integration of CNN and DIC for crack detection*

To evaluate the model's quantitative performance, the annotated dataset was split into 70% training and 30% testing. The CNN achieved a precision of 81.9%, recall of 83.4%, and F1-score of 82.1% in classifying crack regions. These results indicate high reliability in detecting cracks even in early stages, where visible signs are minimal.

Figure 9 shows the predicted crack propagation path over time, with the model accurately identifying the dominant crack trajectory and its direction. Compared to traditional DIC post-analysis that requires thresholding or expert judgment, the CNN model provides automated and reproducible predictions.

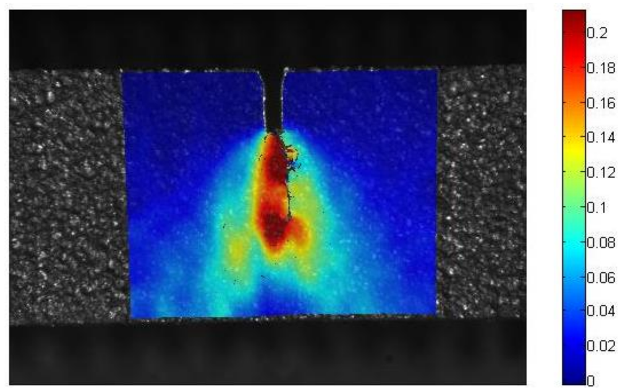


***Figure 9.** Predicted crack propagation path*

Figures 10 and 11 demonstrate the relationship between strain and crack location, as well as the temporal evolution of crack growth. The results align well with the ground truth derived from DIC strain maps, confirming that the model can extract relevant features for damage localization. The computational pipeline developed in MATLAB enables real-time inference at 1 frame per second on a standard desktop without GPU acceleration. This performance demonstrates the system's feasibility for integration into industrial monitoring setups where immediate decision-making is critical.

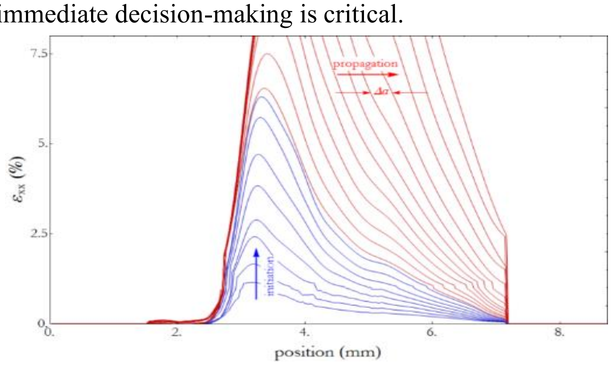


***Figure 10.** Crack–strain correlation*

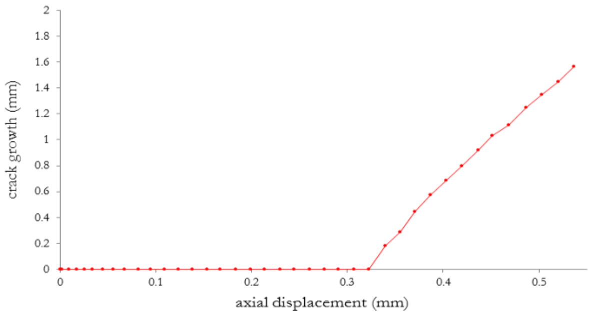


Figure 11. *Crack propagation*

Furthermore, due to its modular structure, the trained CNN model can be retrained or fine-tuned for different materials or testing conditions, offering a scalable solution for predictive maintenance and structural health monitoring.

4. Conclusion

In this study, a Digital Image Correlation (DIC) system combined with Artificial Intelligence (AI) methods was established and implemented to analyze strain and crack propagation in materials. The high-resolution DIC system provided accurate results for the strain field of the specimen, enabling the prediction of crack evolution during testing. By using a computational program, the results obtained from the DIC images allowed the identification of the crack path and analysis of the relationship between crack location and the regions with the highest strain. The images were analyzed and presented clearly, illustrating the crack progression over time.

A key feature of this study is the application of deep learning models, particularly Convolutional Neural Networks (CNN), to identify crack regions and predict crack growth from DIC images.

The CNN model achieved a precision of 81.9%, recall of 83.4%, and F1-score of 82.1%, confirming its capability for early-stage crack detection with high accuracy. Compared to conventional DIC analysis that requires manual post-processing, the proposed method enables automatic, real-time crack identification and reduces dependency on user experience or preset thresholds.

The system was implemented in MATLAB and successfully ran in real time (1 frame per second) on standard computing hardware without GPU acceleration, demonstrating its potential for practical deployment in industrial environments.

Moreover, the model can be easily retrained for different materials or loading conditions, making it adaptable for a wide range of structural health monitoring applications.

In future work, more advanced architectures such as U-Net or Generative Adversarial Networks (GANs) will be explored to improve segmentation precision, enhance robustness under noisy conditions, and support more complex deformation scenarios such as dynamic fatigue or multi-axial loading. Additionally, integration with embedded systems or edge computing devices will be investigated to enable fully autonomous, in-situ crack monitoring systems.

In conclusion, this research has demonstrated the potential of combining DIC and AI for monitoring and predicting crack development, opening up new prospects for the application of advanced technology in materials mechanics analysis and structural maintenance.

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