# iCMAD: Physics-Informed Deep Learning with Digital Image Correlation for Aircraft Crack Monitoring

*Aatif Jamshed[1,2], Shish Ahmad[1,3]*

[1] Lincoln University College, 47301, Petaling Jaya, Selangor D.E., Malaysia; [2] Krishna Institute of Engineering & Technology (KIET), Ghaziabad, Delhi-NCR, Uttar Pradesh, India; [3]Dept. of CSE, Integral University, Lucknow, India

Email: [1,2]09.aatif@gmail.com, [1,3]pdfsv.shish@lincoln.edu.my, [1,3]shish@iul.ac.in

**Abstract:** Crack propagation as a consequence of fatigue in aircraft structure is a long-standing safety issue in the metallic framework, and the present system of checks is based on subjective evaluation and localized sensors, which cannot be extended to large aircraft. In this paper, the multi-task deep learning system iCMAD (Improved Crack Monitoring and Analysis Deep Network) that integrates full-field Digital Image Correlation (DIC) with fracture mechanics constraints to automatically detect cracks, segment them, and locate their tips and predict their growth is presented. iCMAD is based on the previous CMAD architecture and renders the Paris law into a physics-informed loss function, integrates temporal modules of variable amplitudes fatigue spectra, has stereo DIC-capable out-of-plane deformations, and caters to edge hardware via model compression. Comparison of datasets which consist of twelve aluminium 2024-T3 samples in various loading regimes demonstrates fidelity in prediction and close to real time inference on the embedded platforms.

**Keywords**: Structural Health Monitoring; Digital Image Correlation; Physics-Informed Neural Networks; Fatigue Crack Growth; Deep Learning; Aircraft Safety

## Introduction

Service Commercial aircrafts accumulate thousands of pressurizations and loading cycles and the alloy metals used as fuselage skins, wing spars, and bulkheads always develop micro-cracks at the points of stress concentration: holes made by rivets, lap joints and cutouts. Undetected, such defects increase in size during the normal cyclic loading until they become critical, and they pose a risk of extensive failure [1]. Structural Health Monitoring (SHM) can solve this problem by continuously assessing damage, but early implementations of strain gauges, acoustic emission sensors, and periodic ultrasonic tests are only capable of covering defined regions, and cannot immediately give a damage image on a spatially comprehensive scale of the whole structural panel [1].

Digital Image Correlation (DIC) is a non-contact, full-field method providing an alternative measurement that determines surface displacement and strain distributions based on the deformation of speckle pattern of consecutive images, where the resolution is determined by the camera optics and not sensor location [2]. Nevertheless, the DIC fields to actionable crack information translation is still performed by experts and ill adapted to real-time automation [3]. Deep learning has created new opportunities: CNNs provide good results in crack classification and segmentation, recurrent and attention-based models capture the temporal damage dynamics [4]. The previous CMAD model [5] connected DIC to deep learning and was only confirmed on small coupons with constant-amplitude loading and physics-free.

In this paper, iCMAD is proposed that helps to seal multiple gaps by: (a) multi-task architecture to detect, segment, and localize joint cracks; (b) temporal module to predict growth in changing amplitude spectra; (c) physics-informed loss regularization based on Paris law; (d) stereo compatibility of DIC; and (e) model compression to deploy edges.

**Related work**

A systematic search on Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar was kept selecting peer-reviewed articles (2014-2025) on DIC-based crack monitoring, deep learning-based SHM, and physics-informed fracture modelling written in English. The DIC theory was developed by Sutton et al. [2] in the measurement of deformation. Strohmann et al. [3] used the automated multi-scale tracking of crack tip and Melching et al. [4] used ParallelNets to prove that networks can learn fracture-mechanics signatures in DIC fields. Liang et al. [6] predict fatigue crack growth by training spatiotemporal networks on DIC data and Yoon et al. [7] studied deep-learning-based full-field strain reconstructing using sparse sensors. Physics-informed neural networks (PINNs), formalinized by Raissi et al. [8], incorporate governing equations as loss functions but are not yet extensively used when it comes to DIC-based fatigue monitoring. Table 1 consolidates these findings.

*Table 1. Compares this work with the related work or previous research by other researchers*

| Approach | Detect. | Segm. | Growth | Physics | Key Limitation |
|---|---|---|---|---|---|
| DIC fracture (Roux & Hild) | Manual | Manual | Measured | Yes | Expert-dependent, not scalable |
| CNN classif. (Cha et al.) | Yes | No | No | No | No spatial localization or forecast |
| U-Net / CrackNet | Partial | Yes | No | No | No DIC awareness or progression |
| CMAD [5] | Yes | Yes | No | No | Small-scale, purely data-driven |
| PINNs [8] | Partial | No | Partial | Yes | Not tailored to DIC crack tasks |
| **iCMAD (This work)** | **Yes** | **Yes** | **Yes** | **Yes** | **Under experimental validation** |

**Key Contribution**

The contributions take place across five dimensions. To begin with, multi-task learning has in common the spatial representations in detection, segmentation, and localization and provides the benefits of efficiency and mutual regularization. Second, the integration of the law and stress intensity factor relationships of Paris into the training loss eliminates physically invalid predictions. Third, the temporal extension is an extension of the static-Snapshot analysis in importance to growth reasoning over time varying amplitude spectra. Fourth, stereo DIC extends the measurement to the 3/D plane, to the out-of-plane damages in a curved panel. Fifth, the model is compressed through structured pruning and INT8 quantization to run on embedded inference hardware.

**Method, Experiments and Results**

The iCMAD architecture comprises four modules covering the full lifecycle of fatigue crack monitoring. Figure 1 illustrates the overall data flow.

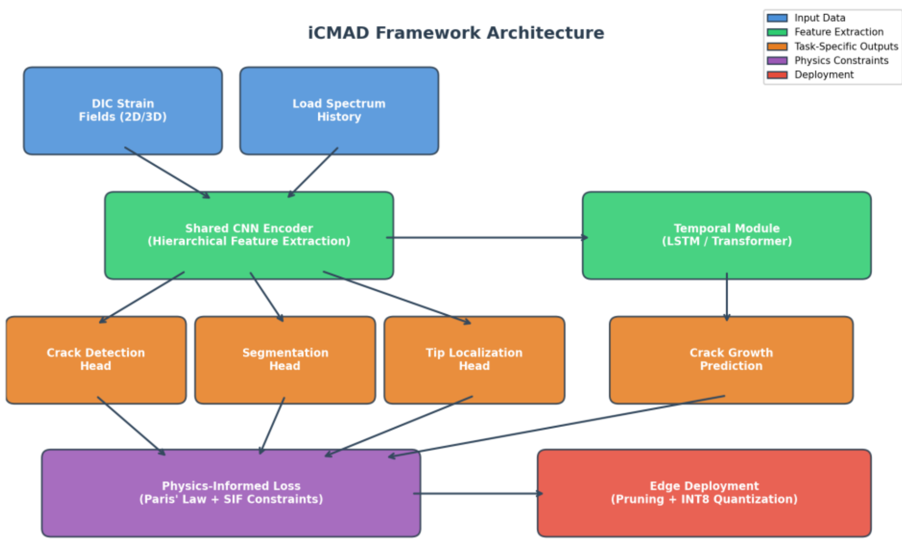


*Figure 1. Schematic of the iCMAD framework: DIC inputs flow through a shared encoder, task-specific heads, temporal module, physics-informed loss, and edge deployment pipeline.*

### *A. Multi-Task Crack Analysis Module*

A joint encoder-decoder CNN takes input of whole-field strain maps of DIC and gathers hierarchical spatial features. The shared representation gives three decoder heads: a binary classifier used to decide when to initiate a crack, a pixel-level segmentation mask used to determine the path of the crack and a regression head used to determine the whereabouts of the crack tip. Representing a similar encoder minimizes parameters and encourages features to be useful in all tasks, which brings about paramount regularization to counteract single-task overfitting.

### *B. Temporal Crack Growth Prediction*

Fields of strain of DIC sequences and the loads are then fed to an LSTM or Transformer model and used to predict further crack length growth. The load input supports variable-amplitude spectra simulating flight profiles high-amplitude take-off and landing periods interspersed with cruise loads helps it overcome a significant limitation of the earlier work that was constant-amplitude only.

### *C. Physics-Informed Constraints*

Composite law in Paris' ($da/dN = C(\Delta K)^m$) is represented as a penalty in the loss functional, which guides the growth predictions into material consistent trajectories. Additional criteria of stress intensity factor and energy release as well reduce non-physic artefacts and promote generalization to otherwise undiscovered loading patterns.

### *D. Stereo DIC and Edge Deployment*

Its input pipeline receives multi-camera rigs (stereo, 3D, DIC) which are used to detect out-of-plane damage on plane aircraft panels, thanks to calibration. Organized channel pruning as well as quantization to INT88 cuts down model size by an estimated 4-8x, and seeks NVIDIA Jetson and FPGA platforms.

### *E. Datasets and Evaluation*

There are two open datasets to work with during training and evaluation. DIC fields of aluminium 2024-T3 CT specimens loaded in constant- and variable-amplitude tests are found in the DIC fields repository [9]. Mendeley Data collection provides DIC fields in block loading. A total of twelve specimens are used to offer varied fatigue regimes. Most of the metrics are IoU and F1-score (segmentation), MAE (tip localization, growth prediction), RMSE (strain reconstruction), and the law consistency of Paris. Edge benchmarks are logs of the Jetson hardware (latency and throughput).

## Discussions

Pooling of gradient information was supposed to be higher in the shared encoder compared to the single-task baselines, since the shared encoder would pool gradient information of the complementary objectives to generate high results on both the IoU and F1. A demand of narrow spatial detail by the segmentation head compels the encoder to maintain spatial detail that is otherwise thrown away by a detection-only network. Figure 2 is a comparison of the projected capability profile of CMAD and that of iCMAD.

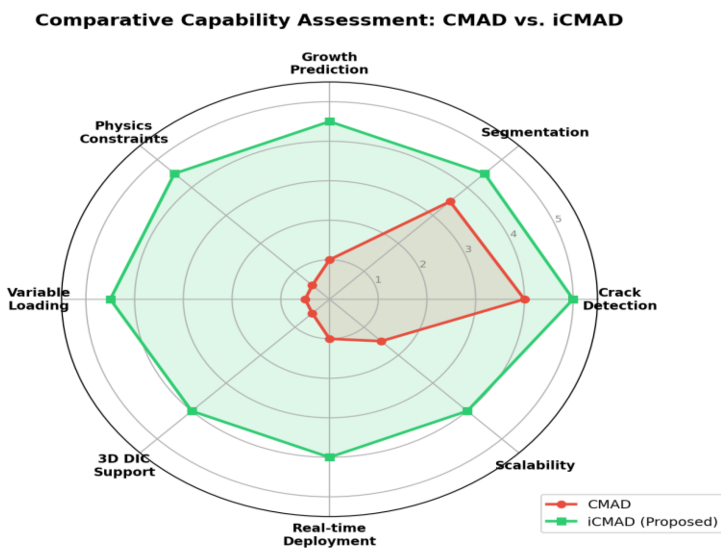


*Figure 2. Capability comparison of CMAD and iCMAD across eight evaluation dimensions. Higher values indicate stronger capability.*

To predict growth when the amplitude of the loading is variable, the physics-informed loss is used as a stabilizing anchor. Models with parameters trained on data of constant amplitude display distribution shift on variable spectra, occasionally predicting non-physical discontinuities in the growth-rate. The law punishments in Paris are limiting the paths of the mechanics in plausible envelopes. The stereo DIC ought to show damage in curved panels beyond the capability of 2D analysis, and compression tests on equivalents of such architectures indicate that 4-8x model reduction can be achieved with acceptable accuracy levels.

## Conclusions

iCMAD is an advanced deep learning framework of automated aircraft SHM that combines full-field DIC and physics-informed fracture mechanics, which was introduced in this paper. The key conclusions are:

- The manual, expert-based DIC interpretation issue has been solved with the help of a single pipeline with the ability to detect cracks, segmentation, localization as well as growth forecasting in one forward pass.
- The law and stress intensity factor limitations of Paris in the loss function allow non-physical forecasting in changing pressure amplitude loading scenarios such as actual flight service.
- The addition of stereo DIC support and edge-device optimization take the framework a step further to be able to demonstrate its capability in the laboratory as well as be utilized in actual aircraft structures.
- It is in current experimental validation on twelve specimens; the direction of future work will be onto full-scale aircraft panel geometries and cross-alloy transfer learning.

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