Dual-modal Defect Detection in Aeroengine Blades: A Comparative Analysis of Deep Learning Architectures using Visual and Active Thermographic Data Fusion

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Abstract

Aeroengine blade inspection is critical but challenging because standard visual inspection cannot detect subsurface defects. To address this, this study proposes an automated, bimodal deep learning framework fusing RGB visual data with Active Infrared Thermography (IRT). Utilizing a CNN architecture on a dataset of paired visual and thermal images, the dual-modal approach is benchmarked against a unimodal ResNet-50 baseline. Results demonstrate that the bimodal framework significantly improves classification accuracy and reduces false negatives for subtle defects. Integrating IRT with visual data provides a robust, synergistic non-destructive testing workflow for aerospace maintenance.

1. Introduction

Aerospace components, particularly aeroengine blades, are subjected to some of the harshest operating environments, including high temperatures, pressures, and centrifugal loads. These conditions often lead to the incursion of defects such as misalignment of ply orientation, voids, matrix cracks, and foreign contaminants. If left undetected, these flaws act as stress concentration points, potentially leading to catastrophic failure.

Technicians and researchers develop and utilize inspection techniques to assist them in identifying all sorts of defects, ranging from cracks and burns to corrosion. Traditionally, inspection of composite materials includes non-destructive testing (NDT). These defect detection tests inspect the soundness and integrity of components without altering or impacting them, directly improving their longevity, reducing safety concerns, and minimizing downtime [1].

Current detection methods, including infrared and ultrasonic testing, can be inconsistent and prone to human error when conducted manually. However, recent advancements in Artificial Intelligence (AI) have expanded the capabilities of quality control, aligning inspection processes with the goals of automated manufacturing. This paper explores a dual-modal approach combining visual and thermal data to bridge the gap between surface-level observation and subsurface integrity, as presented in Figure 1.

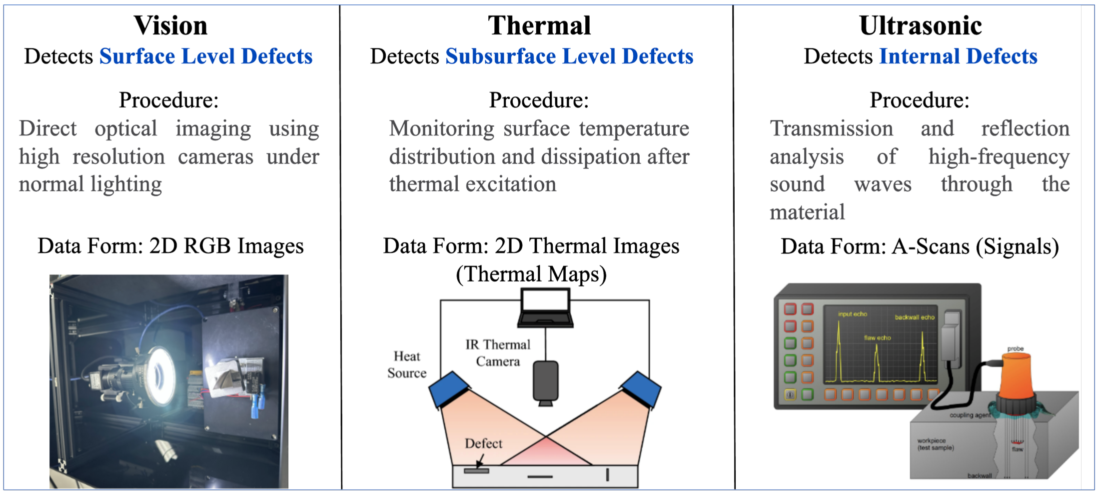

Fig. 1. *Overview of non-destructive testing approaches used for the inspection of defects in aerospace components. The work in this research utilizes visual, thermographic, and ultrasonic data to provide insight into different defect types and locations.*

2. Automated Defect Detection

Automated defect detection is a huge topic of interest and constant advancements. Computer-based defect detection has become one of the key technologies used in intelligent manufacturing [2]. These techniques include machine learning (ML) and deep learning (DL) algorithms. Since its introduction in the 20th century, ML has evolved from its initial applications and resulted in breakthroughs in DL and neural networks [3]. DL can extract defect features on its own, unlike ML, which requires manually designed features. Applications of DL inspection uses in the industry is presented in Table 1.

The framework utilizes a Convolutional Neural Network (CNN) for automated classification. CNNs are specifically designed to recognize patterns and extract features through successive kernels, making them ideal for identifying complex defect geometries. For the dual-modal fusion, the feature maps from the RGB branch and the IRT branch are concatenated at the fully connected layer. This allows the model to calculate a total stress intensity or defect probability based on integrated inputs.

Table 1. *Publications on automated defect detection in composite materials. Highlighting the model, application, and experimental results.*

Ref	Model	Application	Results
[4]	Deep CNN	Catenary support	A mean average precision of 92.16% in detecting fasteners of the cantilever joints.
[5]	Region-CNN	Railway subgrade	Achieved 85.2% precision in detecting ballast fouling, mud pumping, and water abnormality.
[6]	Custom CNN	Gas, water, and oil pipelines	Obtained an accuracy of 98.2% when applied in classifying pipeline corrosion levels.
[7]	VoxNet	Carbon fiber-reinforced polymer	Accuracy of 92.2% in the inspection of drilled hole defects.
[8]	Deep CNN	Aeronautics composite materials	Slag inclusion defects were identified with an accuracy of 96.8%.

3. Conclusion

This study demonstrates that integrating infrared thermography with deep learning creates a robust diagnostic tool. By moving beyond unimodal reliance, the proposed bimodal framework offers a pathway toward more reliable, automated, and non-destructive evaluation workflows for the aerospace maintenance sector. Future work will focus on the deployment of lightweight models for real-time inspection of standardized composite material datasets to alleviate data demand.

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