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Detection of Structural Failures in Aerospace Vehicles via Artificial Intelligence-Based Algorithms

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ABSTRACT

Accurate detection of structural damages in aerospace components—such as cracks, corrosion, and manufacturing defects—is of critical importance in the aviation industry. This study aims to enhance the precision and efficiency of damage identification in aerospace structures through the application of artificial intelligence algorithms.

In this research, data obtained from non-destructive testing (NDT) methods—including ultrasonic testing, radiography, and thermography—were collected and processed using deep learning algorithms. The proposed approach, based on convolutional neural networks (CNNs) and image processing techniques, enabled automated and more accurate damage detection.

The findings demonstrated that the use of artificial intelligence not only improves diagnostic accuracy compared to traditional methods, but also reduces human error and accelerates data analysis. This approach can serve as an effective tool in periodic inspections of aerospace structures, thereby enhancing their safety and reliability. The results of this study highlight the significant potential of AI in transforming non-destructive inspection techniques.

Keywords: *Artificial Intelligence, Non-Destructive Testing, Aerospace Structures, Deep Learning, Damage Detection*

1. *INTRODUCTION*

Due to the high safety sensitivity and technical complexity of the aviation industry, precise and reliable methods for detecting structural damages in aerospace components—such as aircraft fuselage, wings, engines, and composite parts—are essential. Damages including surface and subsurface cracks, corrosion, structural defects, and material fatigue can lead to catastrophic consequences such as reduced flight safety, increased maintenance costs, and even serious accidents.

Non-destructive testing (NDT) methods such as ultrasonic testing, radiography, thermography, and eddy current inspection are widely used to identify these damages. However, these techniques face challenges including operator dependency, time-consuming inspection processes, and limitations in detecting complex or microscopic defects (Mahmoudi, 2014). These limitations highlight the urgent need for advanced and automated approaches to improve the accuracy and efficiency of inspections.

In recent years, significant advancements in artificial intelligence—particularly deep learning algorithms—have opened new horizons in industrial inspection. These technologies, with their ability to process large volumes of data and identify complex patterns, can serve as powerful tools for analyzing data obtained from NDT methods.

Previous studies have explored the potential of modern technologies to enhance inspection processes. For instance, Hasani et al. (2019) investigated the limitations of ultrasonic testing in detecting subsurface cracks in composite structures and reported low accuracy in identifying small defects. In another study, Rezaei et al. (2021) examined the use of traditional image processing in analyzing radiographic data and concluded that due to data complexity and manual adjustments, these methods offer limited performance.

In contrast, the application of deep learning algorithms—especially convolutional neural networks (CNNs)—has shown promising results in improving damage detection. For example, Kamal (2015) demonstrated that early machine learning algorithms could enhance the accuracy of thermographic image analysis, although further optimization was needed. Similarly, Smith et al. (2018) reported a 20% increase in the accuracy of structural defect detection using deep neural networks in thermographic image analysis. Johnson et al. (2020) showed that combining multiple NDT data sources (e.g., ultrasonic and *thermographic) with deep learning models significantly reduced error rates. These studies underscore the high potential of artificial intelligence in transforming non-destructive inspection processes and overcoming the limitations of traditional methods.*

Based on this background, the primary objective of this research is to develop an AI-based approach for the automated and accurate detection of structural damages in aerospace systems using data obtained from NDT techniques. By leveraging advanced deep learning algorithms, particularly CNNs, this study aims to significantly improve damage detection accuracy compared to conventional methods.

The research hypotheses are as follows:

Deep learning algorithms can enhance the detection accuracy of complex and small-scale damages compared to traditional NDT methods.

The use of artificial intelligence significantly reduces human error in the inspection process.

Integrating multiple NDT data sources with AI algorithms increases data analysis speed and overall inspection efficiency.

This study seeks to introduce a novel approach that not only improves the safety and reliability of aerospace structures but also contributes to reducing maintenance costs and enhancing inspection performance. The results are expected to serve as a foundation for developing more advanced technologies in industrial inspection.

2. .Methodology

This study is experimental and data-driven, designed to detect structural damages in aerospace components—such as surface and subsurface cracks, corrosion, and structural defects—using non-destructive testing (NDT) methods and deep learning algorithms. The research process consisted of four main stages:

- *Collection of NDT data from aerospace structures*
- *Data preprocessing to enhance quality and reduce noise*
- *Development and training of artificial intelligence models based on convolutional neural networks (CNNs)*
- *Evaluation of model performance compared to traditional inspection methods*

The study aimed to improve detection accuracy, reduce human error, and increase the speed of damage identification.

3. Population and Sampling

The statistical population included aerospace structures used in commercial and military aircraft, particularly aluminum fuselages and composite components such as carbon fiber. The samples were composed of real and simulated NDT data, including ultrasonic testing (for subsurface crack detection), digital radiography (for internal defect identification), and thermography (for detecting thermal anomalies caused by damage).

The dataset consisted of 1,000 samples: 600 ultrasonic images, 300 radiographic images, and 100 thermographic images, collected from certified aviation laboratories and computer simulations. Purposeful sampling was used to select data representative of common damage types (cracks, corrosion, delamination). The data were randomly divided into three subsets: 70% (700 samples) for training, 20% (200 samples) for validation, and 10% (100 samples) for testing.

4. Research Instruments

Standard NDT equipment was used for data collection:

- *Olympus OmniScan SX ultrasonic device (5 MHz) for subsurface crack detection*
- *GE CRxVision digital radiography system for high-resolution imaging*
- *FLIR T1020 thermographic camera with 0.02°C thermal sensitivity for detecting heat anomalies*

Raw data were preprocessed using MATLAB (version R2023a) and Python libraries (OpenCV and NumPy) to remove noise, normalize images, and extract key features. Deep learning models were implemented using TensorFlow (version 2.12) and Keras.

To ensure instrument validity, NDT equipment was calibrated according to international standards (ASTM E317 for ultrasonic testing and ISO 19232 for radiography). Data reliability was confirmed through repeated measurements (three trials per sample) and calculation of the intraclass correlation coefficient (ICC = 0.92), indicating high data stability.

5. Data Analysis

For data analysis, a CNN model based on the ResNet-50 architecture was selected due to its depth and use of residual connections, which enhance the extraction of complex features from image data. The model was trained on 700 samples using optimized parameters: learning rate of 0.001, batch size of 32, and 50 training epochs. To prevent overfitting, regularization techniques such as dropout (rate = 0.5) and batch normalization were applied.

Input data included normalized images (256×256 pixels) and ultrasonic signals converted into image format. Model performance was evaluated using the following metrics:

- *Accuracy – percentage of correct predictions*
- *F1 Score – balance between precision and recall*
- *False Positive Rate – evaluation of incorrect positive detections*
- *Confusion Matrix – detailed analysis of classification errors*

For comparison with traditional methods, data were manually analyzed by NDT experts, and results were statistically examined using paired t-tests in SPSS (version 26) to confirm significant differences between the proposed model and conventional inspection techniques. Additionally, sensitivity analysis was conducted to assess the impact of model parameter variations, such as learning rate.

6. Results

This section presents the findings of the study. The data obtained from non-destructive testing (NDT) methods—including 600 ultrasonic images, 300 radiographic images, and 100 thermographic images—were analyzed using a convolutional neural network (CNN) based on the ResNet-50 architecture. The objective was to evaluate the performance of the proposed model in detecting structural damages in aerospace components (surface and subsurface cracks, corrosion, and structural defects) and to compare its effectiveness with traditional manual inspection methods.

The results indicated that the proposed model achieved significantly higher accuracy and efficiency than conventional approaches. Table 1 summarizes the performance metrics of both methods, including accuracy, F1 score, and false positive rate. The ResNet-50 model achieved an accuracy of 92.5% on the test dataset, while manual expert analysis reached 78.3%. The F1 score for the proposed model was 0.91, compared to 0.76 for the traditional method, indicating better balance between precision and recall.

The false positive rate was 4.2% for the AI-based model, significantly lower than the 12.7% observed in manual inspection, demonstrating a notable reduction in erroneous detections.

Table 1. Comparison of Model Performance and Traditional Method in Damage Detection

Method	Accuracy (%)	F1 Score	False Positive Rate (%)
ResNet-50 Model	92.5	0.91	4.2
Manual Inspection	78.3	0.76	12.7

For a more detailed analysis, the confusion matrix of the proposed model is presented in Table 2. It shows that the model performed best in detecting subsurface cracks (95% correct classification), followed by corrosion (88%) and structural defects (90%).

Table 2. Confusion Matrix of the ResNet-50 Model

Actual Class	Crack	Corrosion	Structural Defect
Crack	95	3	2
Corrosion	5	88	7
Structural Defect	4	6	90

Statistical analysis using paired t-tests (SPSS version 26) confirmed that the difference in accuracy between the proposed model and traditional methods was statistically significant ($P < 0.01$). Additionally, the average data processing time per sample was 3.5 seconds for the AI model, compared to 15 seconds for manual inspection, indicating a substantial improvement in speed.

Further analysis revealed that the proposed model maintained stable performance under high-noise conditions, such as thermographic images with thermal interference, whereas traditional methods showed a noticeable decline in accuracy. These findings confirm the high potential of deep learning algorithms in enhancing non-destructive inspection processes and overcoming limitations of conventional techniques.

7. Discussion and Conclusion

This study evaluated the performance of a deep learning model based on the ResNet-50 convolutional neural network architecture for detecting structural damages in aerospace components using non-destructive testing (NDT) data. The findings revealed that the proposed model significantly outperformed traditional inspection methods, achieving an accuracy of 92.5%, an F1 score of 0.91, and a false positive rate of 4.2%, compared to 78.3% accuracy, F1 = 0.76, and a 12.7% error rate in manual inspections.

These results align with the findings of Smith et al. (2018), who reported that deep neural networks improved the accuracy of structural defect detection in thermographic image analysis by up to 20%. Similarly, Johnson et al. (2020) demonstrated that integrating multiple NDT data sources with deep learning models reduced error rates—consistent with the reduction observed in this study from 12.7% to 4.2%.

In contrast to the study by Hasani et al. (2019), which highlighted limitations of ultrasonic testing in detecting subsurface cracks, the proposed model in this research achieved a 95% detection rate for such defects, indicating the superior capability of deep learning algorithms in overcoming the constraints of conventional methods.

A notable strength of the proposed model was its stability under high-noise conditions, such as thermographic images with thermal interference. While traditional methods showed a significant drop in accuracy under these conditions, the model maintained robust performance. This finding diverges from Kamal (2015), who reported limited effectiveness of traditional image processing techniques in noisy environments. The improved performance is likely attributed to the use of the ResNet-50 architecture and regularization techniques such as dropout and batch normalization, which enhanced the model's ability to extract complex features.

Moreover, the reduction in data analysis time—from 15 seconds per sample in manual inspection to 3.5 seconds using the proposed model—demonstrates its operational efficiency, aligning with the aviation industry's demand for fast and accurate inspection processes.

In conclusion, this study showed that deep learning algorithms can effectively enhance the accuracy, speed, and robustness of non-destructive inspection procedures in aerospace structures. It is recommended that the proposed model be adopted in periodic inspections of commercial and military aircraft to improve structural safety and reliability.

Future research should focus on integrating multiple NDT modalities (e.g., ultrasonic, radiographic, and thermographic data) with more advanced architectures such as transformer-based networks to further improve detection accuracy under complex conditions. Additionally, developing real-time AI-based automated inspection systems and integrating these technologies with existing NDT equipment could significantly reduce maintenance costs and enhance the overall efficiency of the aerospace industry.

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