International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.70236

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Aircraft Structural Health Monitoring Using Machine Learning

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Abstract: Structural Health Monitoring (SHM) plays a critical role in ensuring the safety and performance of modern aircraft. This review presents a data-driven approach for detecting structural anomalies based on sensor data such as strain, vibration, and temperature. A Random Forest Classifier is employed to differentiate between healthy and damaged states of aircraft structures. By simulating sensor data and applying machine learning techniques, the proposed method demonstrates high accuracy in classifying structural conditions. Visualization techniques such as pair plots and feature importance graphs further enhance the interpretability of the model. This paper also discusses the relevance of SHM in predictive maintenance and provides insights into the use of Python-based libraries including NumPy, pandas, scikit-learn, seaborn, and matplotlib.
Keywords: Structural Health Monitoring, Aircraft Performance, Machine Learning, Random Forest, Predictive Modelling.

I. INTRODUCTION

Modern aircraft rely heavily on structural integrity to ensure safety and performance under extreme environmental and mechanical stresses. Traditionally, SHM has been dependent on scheduled inspections and threshold-based alerts. However, these methods may fail to detect early-stage faults, especially in composite or complex metallic structures. As a result, predictive and automated health monitoring systems have gained importance.

Sensor-based data acquisition combined with machine learning offers a powerful alternative. Features like strain, vibration, and temperature provide quantifiable indicators of structural health. Machine learning models can analyse these indicators to classify the health status of components, enabling real-time diagnostics and reducing the risk of catastrophic failure.

This paper focuses on simulating SHM data and applying a Random Forest Classifier to detect structural damage. The approach highlights the potential of ensemble learning for robust classification and supports early fault detection through visual analytics and feature ranking

II. BACKGROUND AND LEARNING APPROACH

In SHM, sensor readings from aircraft components are analysed to detect anomalies indicative of damage or degradation. These signals often exhibit nonlinear interactions, which makes traditional rule-based systems less effective. Therefore, machine learning techniques—particularly ensemble methods like Random Forest—are utilized for their ability to model complex relationships and handle high-dimensional data.

The method involves the following steps:

1) Data Simulation: Synthetic data is generated for both healthy and damaged conditions using Gaussian distributions to reflect realistic sensor behaviour.
2) Feature Selection: Strain, vibration, and temperature are used as inputs based on their physical relevance to structural integrity. Model Training: A Random Forest Classifier is trained on labelled data, learning the patterns that distinguish healthy from damaged conditions.
3) Evaluation: Classification accuracy, confusion matrices, and feature importance scores are analysed to validate model performance.
4) Visualization: Pair plots and bar charts help in understanding class separability and the influence of individual features.

III. LITERATURE REVIEW

Worden et al. [1] introduced a framework for data-based damage detection using pattern recognition techniques, laying the foundation for supervised and unsupervised learning in structural diagnostics. Their work emphasized the potential of neural networks and support vector machines for classifying damage states using vibration signals.

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Gholizadeh et al. [2] provided a comprehensive review of artificial intelligence applications in SHM, identifying artificial neural networks (ANN), fuzzy logic, and genetic algorithms as key techniques. The study also stressed the importance of feature extraction methods such as Principal Component Analysis (PCA) and wavelet transforms in improving ML model performance.

Zhang et al. [3] employed convolutional neural networks (CNNs) for damage detection in composite structures using Lamb wave signals. Their approach demonstrated high accuracy and robustness in complex, noisy environments, a common challenge in aerospace SHM.

Li et al. [4] proposed a hybrid model combining recurrent neural networks (RNNs) with sensor fusion techniques for aircraft wing monitoring. The model could predict damage progression over time, supporting predictive maintenance strategies. This aligns with the broader shift in SHM from reactive to proactive maintenance paradigms.

Choi et al. [5] utilized autoencoders for anomaly detection in aircraft fuselage structures. The unsupervised learning approach enabled the system to identify abnormal conditions without labelled data, addressing the data scarcity issue often encountered in SHM datasets.

Farrar et al. [6] have highlighted the importance of integrating physics-based modelling with ML techniques, advocating for hybrid systems that ensure interpretability and adherence to physical constraints. This is crucial for safety-critical applications such as aircraft operations.

Gao et al. [7] introduced transfer learning techniques to adapt pre-trained models across different aircraft types and components, significantly reducing the need for extensive retraining and enhancing the scalability of SHM systems.

Sohn et al. [8] pioneered the application of supervised ML in SHM by leveraging classification algorithms to detect structural anomalies based on vibration-based features. Their work highlighted the significance of labelled datasets and feature engineering in training models like Decision Trees and Support Vector Machines (SVM) for precise damage classification.

Kim et al. [9] implemented Convolutional Neural Networks (CNNs) directly on ultrasonic signal images to detect delamination in composite panels. Unlike traditional ML, CNNs eliminate the need for manual feature extraction and offer robust performance under varying noise conditions.

Xu et al. [10] developed an LSTM-based model to monitor crack growth in metallic structures using acoustic emission signals, enabling temporal trend prediction and early failure alerts.

IV. CONCLUSION AND FUTURE SCOPE

This review has explored a supervised machine learning approach for aircraft structural health monitoring using Random Forest Classifiers. By leveraging sensor data and Python based tools, the method provides a highly interpretable and effective framework for distinguishing between healthy and damaged structural states. While the model demonstrates high classification accuracy on simulated data, future work could focus on real-world data acquisition from aircraft testbeds or digital twins. Additionally, expanding the feature set with environmental parameters such as altitude or load conditions may improve generalization. Integration with real-time monitoring systems and cloud-based analytics platforms could further enhance practical deployment, supporting predictive maintenance strategies in aerospace operations. Moreover, combining Random Forests with deep learning architectures or optimizing them with metaheuristic algorithms presents an avenue for achieving higher precision without compromising interpretability. The future of SHM lies in building explainable, scalable, and autonomous diagnostic systems tailored for diverse aircraft environments.

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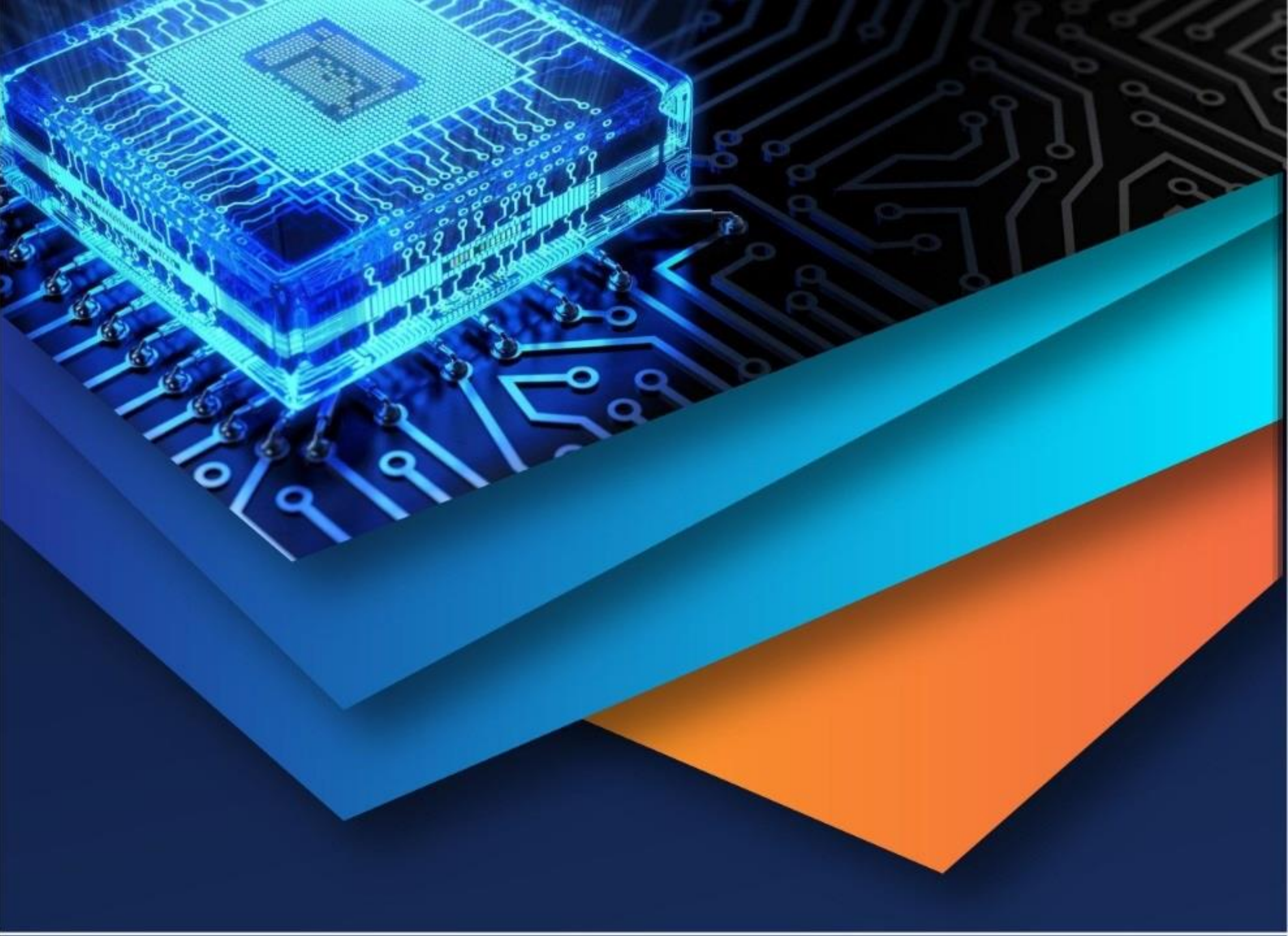

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