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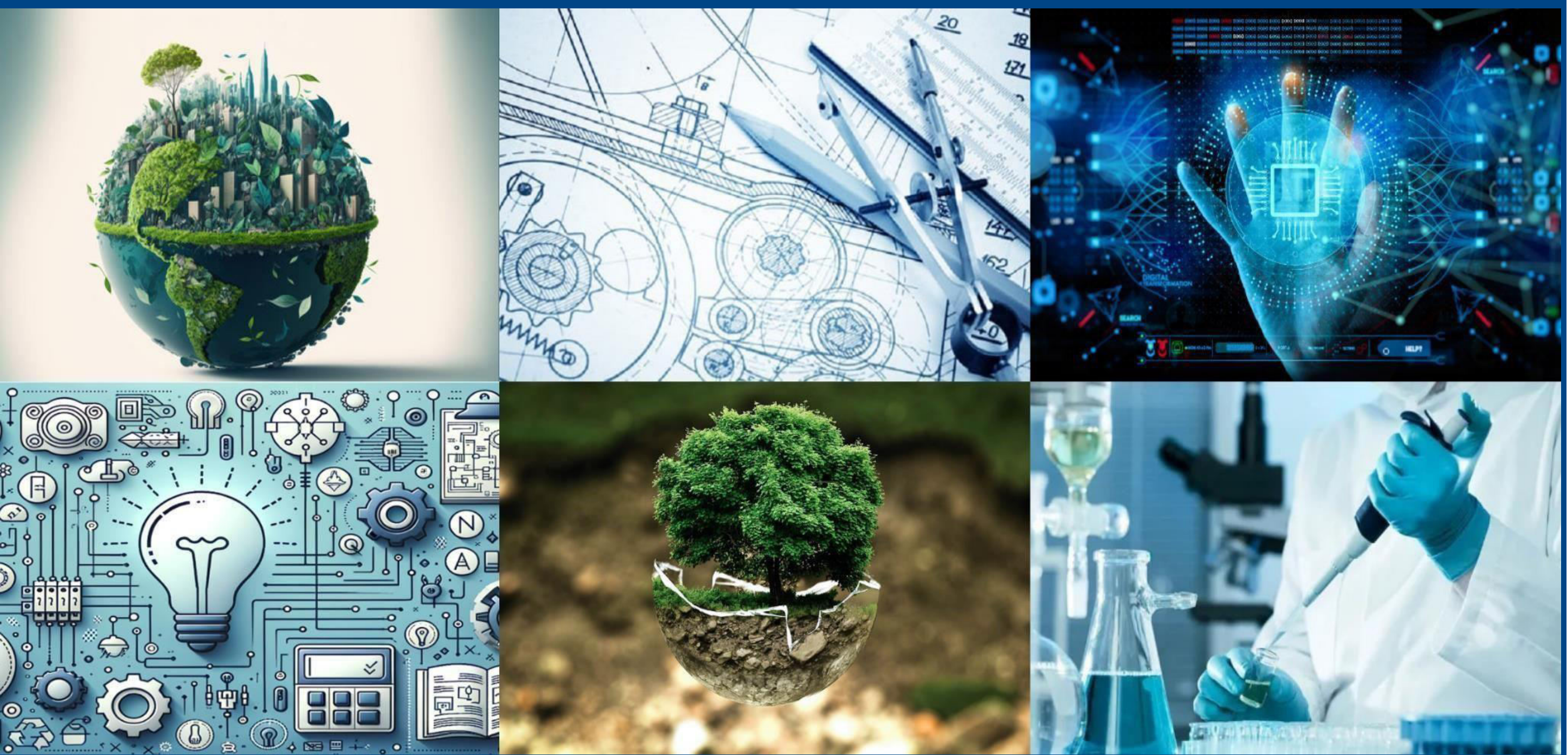

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DEEP LEARNING BASED DEFECT DETECTION FOR LIGHT AIRCRAFT WITH UNMANNED AIRCRAFT SYSTEMS

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ABSTRACT: Visual inspection remains a critical component of aircraft maintenance, traditionally performed by ground personnel through time-consuming and labour-intensive manual procedures, often requiring scaffolding or ladders and susceptible to human error. This study presents a deep-learning-based defect detection framework integrated with an Unmanned Aircraft System (UAS) to enhance inspection efficiency, accuracy, and safety. The proposed system leverages YOLOv8 for object detection, trained on a curated dataset comprising images of light aircraft with various defect types, including damaged and missing rivets, filiform corrosion, and missing panels. Data scarcity challenges were addressed through augmentation strategies and transfer learning with a low-accuracy pre-trained model to expedite labelling. The UAS enables image capture from inaccessible or hazardous areas, while bounding box annotations facilitate precise localisation of defects. Experimental evaluation yielded a validation mean Average Precision (map) of 85%, demonstrating the model's capability to accurately identify targeted defects. The system offers a safer and more efficient alternative to conventional inspections, aligning with aviation maintenance standards. Future work will expand defect categories to include paint chipping, scratches, burns, and rust, thereby broadening operational applicability. This research underscores the potential of combining UAS technology with deep learning to revolutionise preventative aircraft maintenance by mitigating human error and optimising inspection workflows.

KEYWORDS: Aircraft maintenance, defect detection, unmanned aircraft system, YOLOv8, deep learning, computer vision, object detection.

I. INTRODUCTION

Aircraft maintenance is a cornerstone of aviation safety, ensuring that structural integrity and operational reliability are maintained throughout an aircraft's service life. Among various maintenance procedures, visual inspection is one of the most fundamental and frequently employed methods. Traditionally, such inspections are performed manually by ground personnel, involving close physical examination of the aircraft's exterior surfaces, often requiring scaffolding, ladders, and extended time on the tarmac or within a hangar. While these methods are thorough, they are inherently labor- intensive, time-consuming, and prone to human error, particularly in detecting subtle or inaccessible defects.

With the rapid advancements in computer vision and deep learning, automated defect detection has emerged as a viable alternative to manual inspection. Unmanned Aircraft Systems (UAS), equipped with high-resolution imaging sensors, offer the ability to access difficult- to-reach areas, reducing inspection time and minimizing safety risks to maintenance personnel. When integrated with robust deep learning algorithms, such systems can perform real-time detection and classification of structural anomalies, including damaged rivets, missing panels, and corrosion.

Existing research in the field has explored deep learning for damage detection in various engineering domains, such as civil infrastructure, composite structures, and automotive damage assessment. Approaches using architectures like Faster R-CNN, Alex Net, and transfer learning techniques have demonstrated promising accuracy levels. However, these methods face limitations such as insufficient training data, high computational complexity, and performance degradation when applied to unseen or highly variable defect types. Moreover, datasets often suffer from class imbalance and inconsistent labelling, further impacting model reliability.

This research addresses these challenges by proposing a deep learning-based aircraft defect detection system employing the YOLOv8 architecture, optimised for real-time inference and high accuracy in operational environments. The model is trained on an augmented dataset comprising defective and non-defective aircraft images, with pre-processing techniques employed to enhance generalization. The UAS platform enables systematic image acquisition under varying conditions, capturing high-quality visual data from both accessible and hazardous inspection zones.

By integrating UAS technology with state- of-the-art deep learning, the proposed system aims to significantly reduce inspection duration, mitigate human error, and ensure compliance with aviation maintenance standards. The study further demonstrates the system's capacity to detect multiple defect categories with high precision, and outlines pathways for expanding its operational scope to encompass additional defect types such as paint chipping, scratches, burns, and rust. The ultimate goal is to enhance preventative maintenance strategies, thereby improving both safety and operational efficiency in the aviation sector.

II. LITERATURE REVIEW

1.developed a deep learning-based approach for detecting structural damage in buildings, identifying defects such as concrete cracks, steel corrosion, bolt corrosion, and steel delamination. Using a modified Faster Region-Based Convolutional Neural Network (Faster R- CNN) trained on a uniquely labelled dataset, the model achieved a mean Average Precision (map) of 89.7%. The study concluded that dataset expansion and the inclusion of additional defect types could significantly enhance accuracy. The authors also proposed that future work should incorporate Unmanned Aerial Vehicles (UAVs) for automated image acquisition, which could reduce inspection time and increase safety.

2.Fotouhi et al. [7] focused on damage recognition in laminated composite structures, including aircraft components and wind turbine blades, using a pre- trained Alex Net model with transfer learning. Due to the small dataset of 228 images across eight defect categories, image augmentation was employed to prevent overfitting. While the model achieved a validation accuracy of 96.15% for certain defect types, its performance dropped for impact damage classification, yielding only 78% and 73% accuracy for low- and high-energy impacts, respectively. The study emphasized the need for more comprehensive datasets to improve defect classification reliability.

3.A study on vehicle damage detection for insurance claim processing [10] applied various deep learning techniques, including direct CNN training, domain- specific pre-training, transfer learning, and ensemble learning. The researchers created a custom dataset and employed augmentation strategies to improve model generalization. Transfer learning produced the highest performance, achieving 89.5% accuracy. Although focused on the automotive industry, the work demonstrated the transferability of deep learning defect detection methods to other sectors, including aerospace.

4.Malekzadeh et al. [15] presented one of the earliest works on aircraft defect detection, specifically targeting the aircraft fuselage. Their system used a deep neural network for automatic image-based defect identification, achieving an accuracy of 96.37%. While the results were promising, the study did not incorporate UAVs for image capture, which could have enhanced the inspection process by providing access to otherwise difficult-to-reach areas of the aircraft.

5.Donecle, a French start-up, collaborated with researchers to develop a UAV-based deep learning system for aircraft fuselage defect classification [16]. Leveraging few- shot learning techniques, the system addressed challenges of extreme class imbalance, where certain defect categories were rare. While the method proved effective in detecting common defects, its accuracy for rare defect types remained highly dependent on dataset quality and diversity. The study underscored the need for balanced datasets and robust training strategies for comprehensive defect detection in real-world aviation scenarios.

EXISTING SYSTEM

In recent years, deep learning techniques have been increasingly adopted for automated defect detection in various engineering and industrial domains, including structural health monitoring, composite material inspection, and aircraft maintenance. The existing systems primarily rely on computer vision models such as Faster Region-Based Convolutional Neural Networks (Faster R- CNN), Alex Net with transfer learning, and other convolutional neural network (CNN) architectures. These methods have demonstrated promising results in detecting surface anomalies, corrosion, cracks, and other forms of structural degradation.

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In the aviation sector, early research has shown the feasibility of applying deep learning to detect defects in aircraft fuselage images. For example, Malekzadeh et al. developed a deep neural network achieving an accuracy of 96.37% for fuselage defect detection, while the Donecle project demonstrated the potential of UAV-based image acquisition combined with few-shot learning for rare defect classification. In other industries, such as construction and automotive damage assessment, deep learning models have been successfully trained on large, labelled datasets to detect specific defect types with high precision and recall.

Despite these achievements, most existing systems are not optimized for real-time deployment in commercial aviation environments. Many models are trained on limited or domain-specific datasets, which restricts their ability to generalize to diverse aircraft types, varying lighting conditions, and uncommon defect categories. Furthermore, manual data collection and labelling processes remain time-consuming and labor-intensive, limiting scalability for widespread adoption.

Limitations of the Existing System

Although existing deep learning-based defect detection systems have shown promising results in identifying structural anomalies, they face several challenges that hinder their effectiveness in real-world aviation applications. One of the primary issues is the complexity of processing large and high-resolution datasets, which demands significant computational resources and limits the ability to perform real-time inspections. Additionally, the scarcity of high-quality, domain-specific datasets for aircraft defect detection poses a major obstacle. Many available datasets lack diversity, particularly in capturing rare defect types, leading to class imbalance and bias in model performance. This imbalance often results in models that excel at detecting common defects but perform poorly when identifying less frequent or critical anomalies.

Another limitation arises from the heavy reliance on accurately labelled data. Inconsistent or incorrect labelling during the dataset preparation stage can significantly reduce the reliability of model predictions. Furthermore, while UAV-based inspections have been explored in some research, many existing systems still depend on ground-based imaging, restricting the ability to inspect inaccessible or hazardous aircraft areas. Even when UAVs are employed, integration with advanced defect detection models is not always optimized for operational environments. Finally, most existing models are trained on data from specific aircraft types and under controlled conditions, making them less adaptable to different aircraft models, varying lighting conditions, and diverse inspection scenarios. These limitations highlight the need for a more robust, adaptable, and scalable defect detection framework tailored to the demands of the aviation industry.

PROPOSED SYSTEM

The proposed system introduces a deep learning–based aircraft defect detection framework that leverages the capabilities of an Unmanned Aircraft System (UAS) integrated with the YOLOv8 object detection architecture to deliver fast, accurate, and reliable visual inspections. Unlike traditional manual inspection methods, which are time-consuming and prone to human error, this system automates the detection process by capturing high-resolution images of the aircraft exterior using a UAV equipped with an onboard camera. The UAS enables access to hard-to-reach or hazardous areas without the need for scaffolding or ladders, thereby improving safety for maintenance personnel while ensuring comprehensive coverage of the aircraft structure.

The core of the defect detection process is the YOLOv8 model, which has been trained on a curated and augmented dataset containing both defective and non- defective aircraft images. The dataset includes common defect categories such as damaged or missing rivets, filiform corrosion, and missing panels, with future extensions planned for paint chipping, scratches, burns, and rust. Data scarcity issues are addressed through augmentation techniques, including rotation, scaling, flipping, and color adjustments, which increase dataset diversity and improve the model's generalization to new inspection scenarios. To accelerate the labelling process for novel defect categories, a low-accuracy pre-trained model is employed to provide initial bounding box suggestions, which are then verified and corrected by human annotators.

During operation, the UAV systematically scans the aircraft's exterior, capturing overlapping high-resolution images. These images are processed in real time by the YOLOv8 detection engine, which identifies defects using bounding boxes and confidence scores. This approach allows inspectors to quickly verify and priorities repair tasks based on the location and severity of detected defects. The lightweight and optimized nature of YOLOv8 ensures high inference

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speed,enabling near real-time defect detection without requiring excessive computational resources.

By combining UAV-based image acquisition with a robust deep learning model, the proposed system directly addresses the limitations of existing approaches. It eliminates the need for manual inspections in hazardous zones, reduces dependency on excessively large datasets through augmentation, and mitigates class imbalance by incorporating diverse training samples. Furthermore, the adaptability of the YOLOv8 architecture allows for retraining on new aircraft models and environmental conditions, ensuring consistent performance across different operational contexts. Ultimately, this system offers a safer, faster, and more accurate alternative to conventional aircraft inspection methods, aligning with industry standards and supporting preventative maintenance strategies in modern aviation.

Advantages

The proposed system offers several significant advantages over traditional manual inspection methods and existing automated approaches. By integrating an Unmanned Aircraft System (UAS) with the YOLOv8 deep learning framework, the solution enables faster and more accurate defect detection while ensuring safety and operational efficiency. The use of UAV- based imaging allows maintenance teams to inspect hard-to-reach and hazardous areas of the aircraft without physical intervention, reducing the risk to personnel and eliminating the need for scaffolding or ladders. This aerial inspection capability ensures comprehensive coverage of the aircraft's surface, including critical structural zones that may be overlooked during manual checks.

The adoption of YOLOv8 provides a lightweight yet powerful object detection architecture capable of delivering high detection accuracy with rapid inference speeds, making it suitable for near real- time inspection workflows. Data augmentation techniques enhance the robustness of the model, allowing it to generalise well across varying environmental conditions, lighting situations, and aircraft types. Furthermore, the use of a pre-trained low-accuracy model for initial labelling accelerates the dataset preparation process, enabling the system to adapt quickly to new defect categories without extensive manual annotation.

By overcoming common challenges such as class imbalance, limited dataset availability, and labelling inefficiencies, the proposed system ensures high reliability in detecting both common and rare defects. Its adaptability across different aircraft models and operational environments makes it a scalable solution for diverse aviation maintenance needs. Overall, this approach significantly reduces inspection time, enhances defect detection precision, and aligns with preventative maintenance strategies to improve aircraft safety and operational readiness.

III. SYSTEM ARCHITECTURE

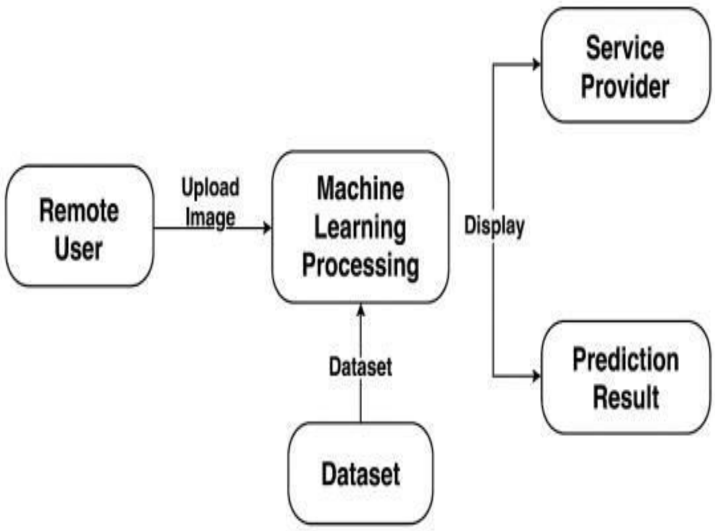

Fig 1. System Architecture

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IV. MODULE DESCRIPTION

The proposed aircraft defect detection system is designed with a modular architecture to ensure scalability, adaptability, and efficient workflow management. The system comprises two primary operational roles: the **Remote User** and the **Service Provider**, each supported by dedicated modules that handle specific functionalities.

The **Remote User Module** is responsible for managing end-user interactions with the system. This module allows authenticated users to create and update their profiles, upload aircraft inspection images, and access the prediction interface. Within the prediction page, users can submit new images captured by the UAV for defect analysis. Once processed by the YOLOv8 detection engine, the results are displayed with bounding box annotations and confidence scores, indicating whether the detected condition is classified as "high" or "low" severity. This module is designed with an intuitive front-end interface to ensure ease of use for inspection personnel, even in time- sensitive operational environments.

The **Service Provider Module** serves as the administrative and data management backbone of the system. It enables the management of all user accounts, storage of trained datasets, and maintenance of historical prediction results. Administrators can monitor prediction accuracy, visualize model performance through graphs, and download datasets for further analysis or retraining purposes. This module also provides access to detailed statistical reports on defect occurrences, model accuracy trends, and system usage metrics. Additionally, it facilitates the review of all remote users' uploaded data to ensure compliance with aviation safety standards and operational requirements.

Both modules work in close integration with the **Machine Learning Processing Module**, which forms the computational core of the system. This component handles image pre-processing, model inference, and result generation. Using the YOLOv8 object detection architecture, the module processes UAV-acquired images, applies bounding box annotations, and generates defect classification outputs in real time. The integration of data augmentation techniques ensures the model's robustness against variations in lighting, weather, and image resolution, making the system reliable across different inspection conditions.

By structuring the system into well- defined modules, the proposed approach ensures efficient division of responsibilities, smooth data flow, and flexibility for future enhancements such as the inclusion of new defect categories or integration with cloud-based analytics platforms. This modular design not onlystreamlines current operations but also supports the long-term scalability of the defect detection framework in diverse aviation maintenance contexts.

V. RESULT

The implementation of the proposed deep learning–based defect detection system using YOLOv8 integrated with an Unmanned Aircraft System (UAS) has demonstrated promising results in enhancing the speed, accuracy, and safety of aircraft visual inspections. The system was trained and validated on an augmented dataset containing images of light aircraft with multiple defect categories, including damaged or missing rivets, filiform corrosion, and missing panels. Through data augmentation techniques such as rotation, scaling, flipping, and colour adjustment, the dataset size was effectively increased, enabling the model to generalise well across varying operational conditions.

Experimental evaluation revealed that the trained YOLOv8 model achieved a validation mean Average Precision (mAP) of 85%, indicating strong detection capability across the targeted defect categories. The inference time per image was significantly reduced compared to conventional deep learning models, allowing near real-time analysis during UAV-assisted inspections. The use of bounding box annotations enabled precise localization of defects, facilitating easier verification by maintenance personnel. The system also proved effective in capturing images from inaccessible or hazardous areas of the aircraft without compromising personnel safety, demonstrating the operational advantage of UAS deployment

In practical testing scenarios, the proposed system successfully reduced inspection time while maintaining high accuracy in defect detection. Compared to traditional manual inspections, which are labor- intensive and prone to human error, the automated approach provided consistent and repeatable results. The capability to adapt to different aircraft models through retraining further highlights its scalability. These results confirm that integrating UAV-based imaging with an optimized YOLOv8 framework can significantly improve preventative maintenance processes, reduce operational downtime, and enhance overall aviation safety standards.

VI. CONCLUSION

This research presents a deep learning– based defect detection system for light aircraft, integrating the YOLOv8 object detection framework with an Unmanned Aircraft System (UAS) to enhance the efficiency, accuracy, and safety of visual inspections. The proposed approach addresses the limitations of traditional manual inspections by enabling automated, high-resolution image capture of aircraft surfaces, including hard-to-reach or hazardous areas, without exposing maintenance personnel to unnecessary risks. The use of data augmentation and transfer learning techniques effectively mitigated dataset limitations, improving the model's generalisation capabilities across varying lighting conditions and defect types.

The experimental results demonstrated a validation mean Average Precision (map) of 85%, confirming the system's ability to accurately detect defects such as damagedor missing rivets, filiform corrosion, and missing panels. The deployment of bounding box–based visualization facilitated precise defect localization, enabling faster decision-making for maintenance actions. The system also achieved significant reductions in inspection time compared to conventional methods, while maintaining consistent detection performance across multiple test scenarios.

Overall, the integration of UAV-based imaging with a robust YOLOv8 architecture represents a practical and scalable solution for modern aircraft maintenance. By reducing reliance on manual inspections, minimizing human error, and enabling preventative maintenance strategies, the proposed system contributes to improved operational readiness and enhanced aviation safety. Future developments will focus on expanding the defect categories to include paint chipping, scratches, burns, and rust, as well as integrating cloud-based analytics for centralized inspection data management.

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