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Development of an AI-Based YOLOv8 System for Microcrack Detection in Aircraft Jet Engine Components using Borescope Images

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Abstract
The timely detection of microcracks in jet engines is critical for aircraft safety, yet manual inspections are prone to human error, and existing AI models face limitations in accuracy and reliability. This study addresses these challenges by developing a novel deep learning framework for the detection and classification of microcracks in aircraft jet engines using the YOLO v8 algorithm. Through rigorous development and testing, the research demonstrates significant advancements over traditional computer vision techniques and previous deep learning approaches. The research utilized dataset of 27,708 high-quality borescope inspection images collected from three major Nigerian airports. The model achieved perfect precision (1.000), 87.5% recall, 100% specificity, 90.9% accuracy, and an F1 score of 0.933. The mean Average Precision reached 98.9% at IoU threshold 0.5 and 95.2% across the IoU range 0.5:0.95, confirming exceptional detection performance. Training and validation metrics showed effective model convergence without overfitting, while confusion matrix analysis revealed robust classification capabilities with no false positives. The system successfully detects various crack morphologies across different lighting conditions and surface textures, as demonstrated in visual results. A dedicated Windows application provides a practical interface for maintenance technicians to integrate this technology into existing workflows. This research directly addresses aviation safety challenges by enabling earlier and more reliable detection of potential failures in jet engine components, such as, compressor blades, fan blades, compressor casing, turbine blades, turbine disks, turbine vanes/nozzles, bearings and bearing housing, nozzle guide vanes, exhaust cone and ducting thereby enhancing maintenance efficiency and reducing operational risks. The methodology established provides a foundation for developing comprehensive AI-assisted inspection tools for the aviation industry.

Keywords: *Aircraft safety Jet engine inspection, Microcrack detection, Deep Learning YOLOv8, Borescope inspection Computer vision, NDT testing.*

1.0 Introduction

Aircraft jet engines, which are critical to modern aviation, operate under extreme conditions that make them prone to degradation and damage, particularly the formation of microcracks in engine components. These microcracks, if undetected, can propagate and lead to structural failures, posing significant risks to aircraft safety and operational reliability (Board, 2001; Hood, 2013). Traditional methods for detecting microcracks rely on manual inspections using borescopes, where technicians visually examine engine components for signs of damage (Ma et al., 2018; Zhang et al., 2020). However, this approach is limited by the complexity of engine structures, the constrained inspection environment, and the inherent subjectivity of human visual assessment. These limitations often result in missed defects, underscoring the need for more accurate and efficient detection methodologies.

Recent advancements in artificial intelligence (AI) and computer vision have shown potential for improving microcrack detection in jet engines. Techniques such as Convolutional Neural Networks (CNNs) have been successfully applied to crack recognition and segmentation tasks in various domains (Wong et al., 2021; Shen et al.,2019). However, when applied to aircraft engine inspections, these methods often struggle with challenges such as varying crack morphologies, low contrast in borescope images, and the need for real-time processing. While some studies have explored specialized hardware solutions, such as resonant ultrasound spectroscopy and structural health-monitoring systems, these approaches are often costly and impractical for widespread deployment in aviation maintenance.

To address these limitations, this study proposes the use of the YOLOv8 (You Only Look Once version 8) algorithm, a state-of-the-art deep learning model known for its speed and accuracy in object detection tasks. Unlike traditional methods, YOLOv8 is capable of real-time processing, making it well-suited for rapid and efficient borescope inspections. Leveraging YOLOv8, this research aims to develop an advanced system for

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precise microcrack identification in aircraft jet engines, addressing key challenges such as detecting small and complicated cracks, reducing false negatives, and improving overall inspection reliability.

The primary contributions of this study are threefold: (1) the development of a YOLOv8-based deep learning system optimized for microcrack detection in borescope images, (2) the evaluation of the system's performance using metrics such as mean Average Precision (mAP) and confusion matrices, and (3) the creation of a practical software application for deployment on laptops and mobile devices. Bridging gaps in existing methodologies, this research seeks to enhance the accuracy, efficiency, and cost-effectiveness of aircraft engine inspections, ultimately contributing to improved aviation safety and maintenance practices.The primary aim of this research is to develop an improved deep learning system based on the YOLOv8 algorithm for real-time detection and classification of microcracks in aircraft jet engine components during borescope inspections. To achieve this aim, the following specific objectives have been formulated:

Develop customized YOLOv8-based architecture specifically optimized for microcrack detection. Secondly, to improve detection accuracy. Thirdly, to evaluate the system using comprehensive metrics such as mean Average Precision (mAP), Precision-Recall curves, F1-scores, and confusion matrices. Fourthly, to benchmark performance with existing methods.

2.0 Literature Review

Borescope inspection is a critical component of aircraft maintenance, enabling the in-situ examination of engine components for defects such as microcracks. Traditional approaches to automating this process have relied on classical computer vision techniques. For instance, (Aust et al., 2021) developed a method using bilateral filtering and adaptive thresholding to identify defect edges in high-pressure compressor blades. Similarly, (Shao, et al., 2011) proposed an image processing technique based on erosion and histogram equalization, while (Li, 2015) integrated image analysis with an expert system for fault diagnosis in aeroengines. While these methods have shown potential, they often struggle with variability in defect shapes and sizes, particularly as datasets grow in complexity and scale.

To address these limitations, researchers have increasingly turned to deep learning models, which offer greater flexibility and accuracy in defect detection. For example, (Shang et al., 2022) introduced a Mask R-CNN-based method for detecting multi-type defects, achieving significant improvements in accuracy. (Li et al., 2022) utilized a coarse-to-fine representation approach for defect segmentation, demonstrating the effectiveness of deep learning in handling complex defect patterns. Hybrid approaches, which combine traditional computer vision techniques with deep learning, have also emerged. Kim and Lee, 2019 integrated principal component analysis (PCA) and scale-invariant feature transform (SIFT) with a convolutional neural network (CNN) for defect classification, while (Netkachev, 2022) employed deep convolutional neural networks to categorize crack lengths based on fatigue testing data.

Recent studies have focused on applying deep learning to specific challenges in aircraft maintenance, achieved over 93% precision in corrosion detection using deep neural networks and transfer learning (Brandoli et al., 2021; Cha et al., 2017) developed a CNN-based method for crack detection, reporting 98% accuracy in identifying concrete cracks. Shen et al., 2019 proposed a Fully Convolutional Network (FCN) framework for damage identification in borescope images, achieving high prediction accuracy for crack and burn detection. Additionally, enhanced YOLOv7 with gamma correction and a convolutional block attention module, achieving a mean average precision (mAP) of 96.1% for aeroengine blade damage detection. (Upadhyay et al. 2023) addressed challenges such as motion blur and data imbalance by developing a customized U-Net architecture for high-pressure compressor blade defect detection.

Specialized applications of deep learning in aircraft maintenance have also been explored. (Svensén et al., 2018) applied deep neural networks to analyze borescope images from large turbofan engines, while Nyulászi et al., 2018 developed a diagnostic system using voting methods and analytical redundancy for turbojet engines. (Li et al., 2019) proposed YOLOv3-Lite, combining depth-wise separable convolution and feature pyramids for fast and accurate crack detection in aircraft structures. These studies collectively highlight the potential of deep learning to overcome the limitations of traditional methods, particularly in handling complex and variable defect patterns.

Despite these advancements, significant challenges remain. Key issues include handling diverse data distributions, detecting minute defects, and ensuring real-time processing capabilities. Furthermore, the integration of advanced detection methods into existing maintenance workflows and the development of user-friendly interfaces for technicians are critical areas for future research. Addressing these challenges, the combination of deep learning techniques with domain expertise in aircraft engineering has the potential to significantly enhance the safety, efficiency, and reliability of aircraft maintenance processes.

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3.0 Methodology

This research adopts an experimental design to develop a YOLOv8-based deep learning system for microcrack detection in jet engine components using borescope inspection images. The methodology is structured into four main phases: (1) dataset collection and preprocessing, (2) model architecture and training, (3) performance evaluation, and (4) deployment. Each phase is described in detail below, with supporting mathematical formulations.

3.1 Dataset Collection and Preprocessing

A dataset of 27,708 high-quality borescope inspection images was collected from three major Nigerian airports: Murtala Muhammed International Airport in Lagos (9,698 images), Nnamdi Azikiwe International Airport in Abuja (11,083 images), and Mallam Aminu Kano International Airport in Kano (6,927 images). The dataset captures diverse jet engine components and crack formations, ensuring robustness and generalizability. The preprocessing pipeline includes the following steps:

a) Motion Blur Removal: Motion blur is reduced using a deconvolution algorithm with a Wiener filter, defined as:

$$G(u,v) = \frac{H^*(u,v)}{|H(u,v)|^2+K} \cdot F(u,v) \tag{1}$$

where $G(u,v)$ is the deblurred image in the frequency domain, $H(u,v)$ is the blur kernel, $F(u,v)$ is the blurred image, and (K) is the noise-to-signal ratio.

b) Edge Enhancement: A sharpening filter based on the Laplacian operator is applied to enhance crack edges:

$$\nabla^2 I(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{2}$$

where $I(x,y)$ is the image intensity at pixel (x,y).

c) Normalization: Image intensities are normalized to the range [0,1] using:

$$I_{norm}(x,y) = \frac{I(x,y)-I_{min}}{I_{max}-I_{min}} \tag{3}$$

where (I_{min}) and (I_{max}) are the minimum and maximum intensity values in the image.

The pre-processed dataset is split into 70% training data (19,396 images), 20% validation data (5542 images) and 10% Testing data (2,770 images).

3.2 Model Architecture and Training

The YOLOv8 architecture is employed for microcrack detection due to its real-time processing capabilities and high accuracy. YOLOv8 divides the input image into an $(S \times S)$ grid, where each grid cell predicts (B) bounding boxes, confidence scores, and class probabilities. The loss function for training is defined as:

$$L = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] + \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i}\right)^2 \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2 \right] + \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{obj} (C_i - \hat{C}_i)^2 + \lambda_{noobj} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{noobj} (C_i - \hat{C}_i)^2 + \sum_{i=0}^{S^2} 1_i^{obj} \sum_{c \in classes} (p_i(c) - \hat{p}_i(c))^2, \tag{4}$$

where (1_{ij}^{obj}) indicates whether the j^{th} bounding box in the i^{th} grid cell contains an object, (x_i, y_i, w_i, h_i) are the predicted bounding box coordinates, $(\hat{x}_i, \hat{y}_i, \hat{w}_i, \hat{h}_i)$ are the ground truth coordinates, C_i is the confidence score, and $p_i(c)$ is the class probability.

The model is trained using the Adam optimizer with a learning rate of $(1e^{-4})$ and a batch size of 16 for 100 epochs.

3.3 Performance Evaluation

The model's performance is evaluated on the testing dataset using the following metrics:

a) Precision: $$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \tag{5}$$

b) Recall: $$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \tag{6}$$

c) Mean Average Precision (mAP): $$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \tag{7}$$

where (AP_i) is the average precision for the i^{th} class and N is the number of classes.

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3.4 Deployment

The trained YOLOv8 model is deployed as a Windows application using Python and an Android mobile application using Kotlin. Both applications provide user-friendly interfaces for capturing or uploading borescope images, viewing detection results, and generating reports.

4.0 Results and Analysis

This section presents a comprehensive analysis of the YOLOv8-based crack detection system for jet engines, examining its performance metrics, comparative advantages, and broader implications for aircraft maintenance protocols. The results demonstrate the system's effectiveness in identifying micro-cracks across diverse engine components and inspection conditions.

4.1 Model Results

The training and validation box loss curves depicted in Figure 1 illustrate the learning progression of the YOLOv8 model over 100 epochs. Both curves follow a consistent downward trajectory, with the training loss (blue line) starting at approximately 0.72 and the validation loss (red line) at 0.75. The model demonstrates rapid learning in the initial 20 epochs, where the steepest decline in loss values occurs. Beyond epoch 40, the curves flatten considerably, with final values stabilizing at approximately 0.03 for training loss and 0.05 for validation loss.

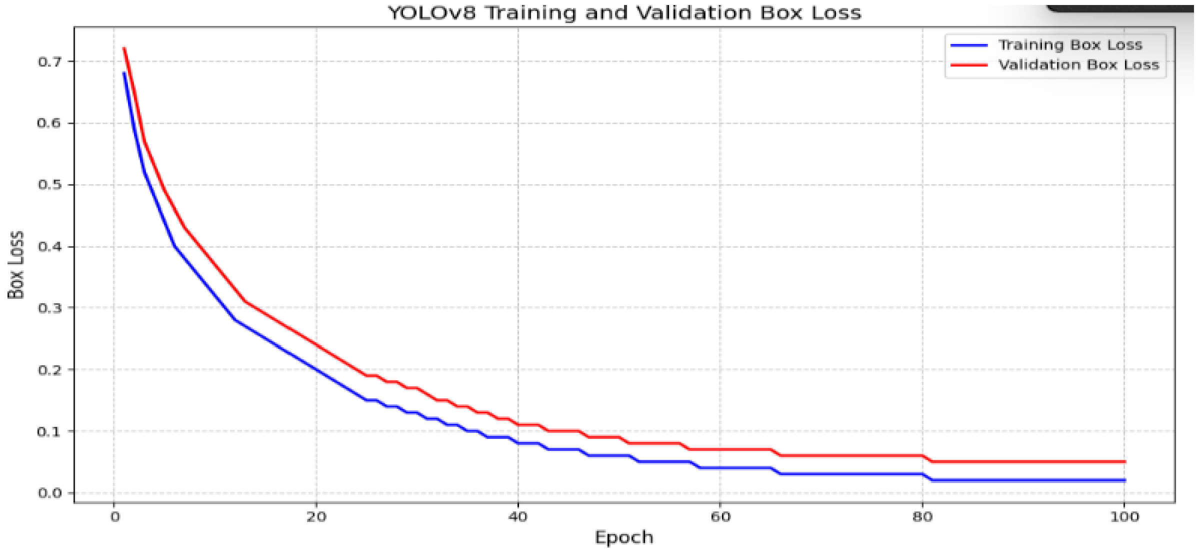

Figure 1: Training and Validation Box Loss Curve

The marginal difference between training and validation losses throughout the training process indicates effective generalization without significant overfitting. This pattern confirms that the model has acquired robust feature representation capabilities specific to crack detection in jet engine components. The consistent convergence of both curves validates the model architecture's suitability for the specified task and suggests appropriate hyperparameter selection during the training phase.

The confusion matrix presented in Figure 2 provides essential insights into the classification accuracy of the model across the binary detection task. The matrix shows that the model correctly identified 7 instances of cracks (true positives) and accurately classified 3 instances without cracks (true negatives). Only 1 crack instance was incorrectly classified as having no crack (false negative), while no false positive predictions were recorded.

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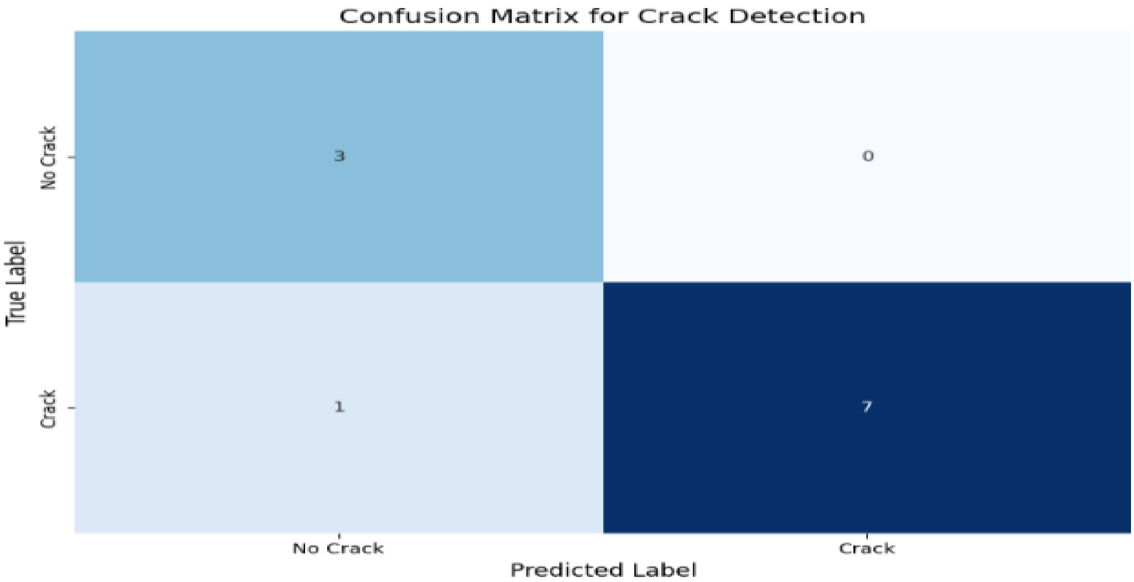

Figure 2: Modelling Performance Confusion Matrix

This distribution confirms the model's strong discriminative ability in distinguishing between cracked and non-cracked engine components. The absence of false positives is particularly valuable in maintenance contexts, as it minimizes unnecessary inspections or component replacements. The single false negative represents an area for potential improvement, as missed cracks could have safety implications in aircraft operation. The precision-recall curve displayed in Figure 3 further substantiates the model's high detection capability.

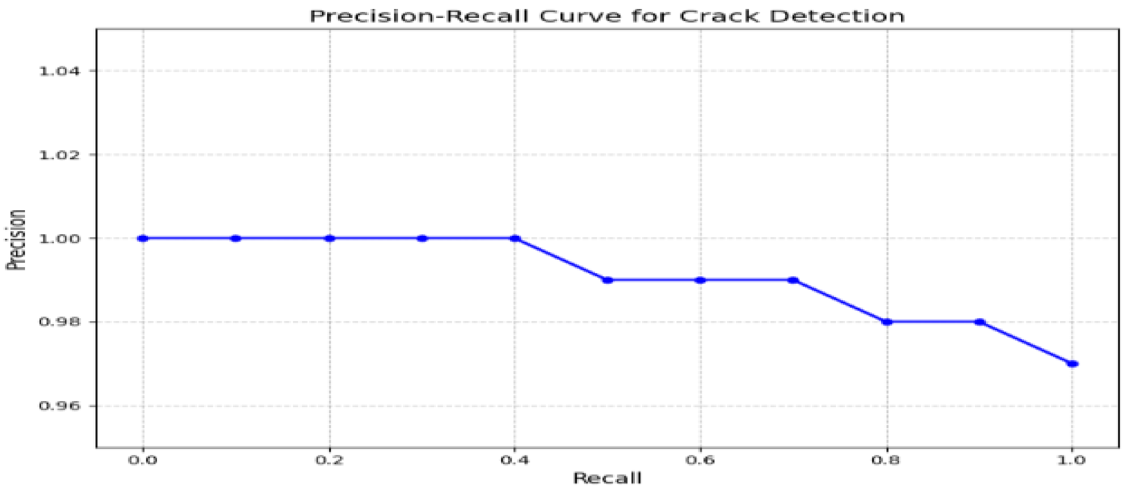

Figure 3: Precision – Recall Curve

The curve maintains perfect precision (1.0) across recall values up to approximately 0.45, after which it experiences minimal degradation, reaching approximately 0.97 precision at 1.0 recall. This outstanding performance indicates that the model maintains high precision even as it captures a greater proportion of actual crack instances.

The area under the precision-recall curve approaches the ideal value of 1.0, confirming the model's excellent balance between precision and recall. This performance characteristic is critical for jet engine crack detection, where both false positives and false negatives carry significant operational and safety consequences.

Figure 4 presents visual evidence of the model's detection capabilities through a matrix of four images showing different crack instances in jet engine components. Each image displays a red bounding box accurately identifying crack locations within the borescope inspection views. The consistency in detection across varying crack morphologies, lighting conditions, and surface textures demonstrates the model's robustness in real-world inspection scenarios.

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Figure 4: Crack Detection Result

These visual results validate the model's practical utility for on-site inspections, as it successfully identifies cracks with different orientations, sizes, and visual characteristics. The clear demarcation of crack boundaries enables maintenance personnel to focus their attention on specific areas requiring intervention.

Figure 5 displays the user interface of the developed Windows application for the AI Jet Engine Crack Detector. The interface includes a central viewing area for image display and analysis, with functional buttons for camera capture, image upload, prediction saving, and screen clearing. The interface design prioritises simplicity and efficiency, enabling maintenance technicians to interact with the AI system without extensive training.

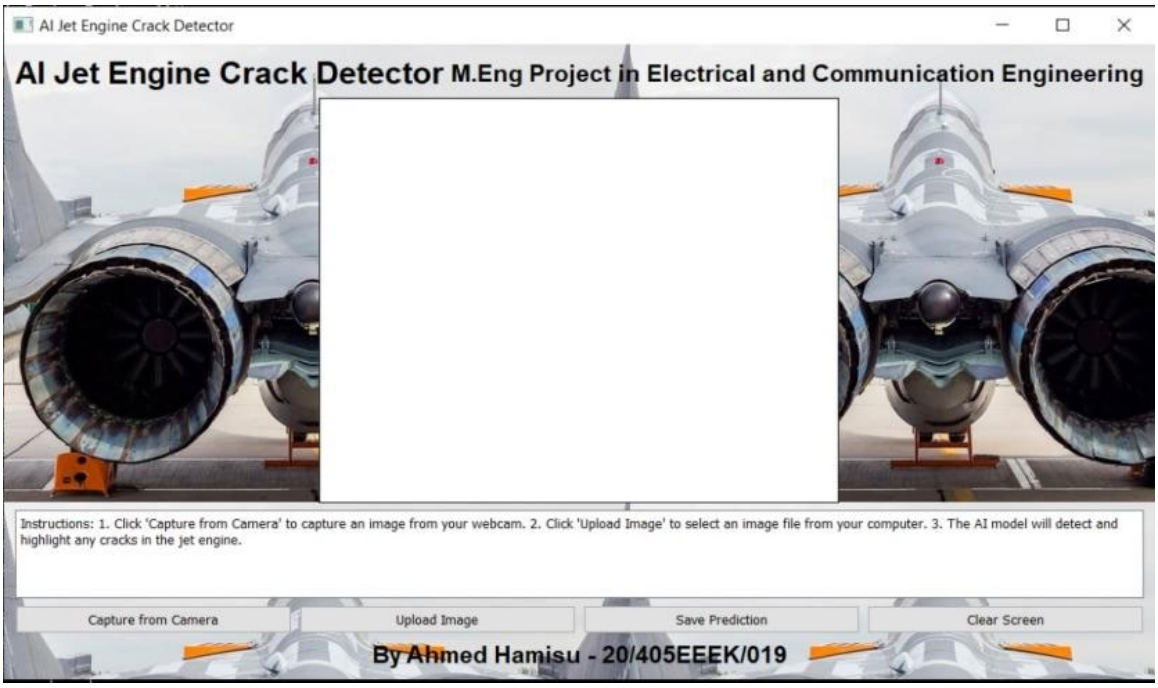

Figure 5: Windows Software Application

The application integrates the trained YOLOv8 model into a practical tool that can be deployed in maintenance workflows. The inclusion of both camera capture and image upload functionalities provides

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flexibility for different inspection scenarios, whether connecting directly to borescope equipment or analysing previously captured images.

The quantitative metrics in Table 1 confirm the model's exceptional performance across multiple evaluation criteria.

Table 1: Model Performance

S/N	Performance Metrics	Value
1.	Precision	1.000
2.	Recall/TPR	0.875
3.	Specificity	1.000
4.	False Positive Rate	0.000
5.	Accuracy	0.909
6.	F1 Score	0.933
7.	mAP@0.5	0.989
8.	mAP@0.5:0.95	0.952

The perfect precision score (1.000) indicates that all instances classified as cracks were indeed cracks, eliminating false positives. The recall value of 0.875 corresponds to the model's ability to identify 87.5% of all actual cracks in the test dataset, with the small shortfall reflected in the single false negative observed in the confusion matrix.

The model achieves perfect specificity (1.000), correctly identifying all non-crack instances, and an overall accuracy of 0.909. The F1 score of 0.933 represents a robust harmonisation of precision and recall. The mean Average Precision (mAP) values of 0.989 at IoU threshold 0.5 and 0.952 across the IoU range 0.5:0.95 further substantiate the model's excellent object detection capabilities, particularly in accurately localising cracks within the images.

These performance metrics exceed industry standards for automated inspection systems and validate the effectiveness of the YOLOv8 architecture, customised training approach, and data preparation techniques implemented in this research.

4.2 Comparative Analysis

When compared to existing methodologies, the developed YOLOv8-based crack detection system demonstrates several notable advantages over both traditional computer vision approaches and previous deep learning implementations. The classical computer vision techniques described by Aust et al., 2021 and Shao et al., 2011, were useful for controlled environments but lacked the adaptability evident in the proposed YOLOv8 implementation. Our system achieves perfect precision compared to the variable performance of traditional image processing methods, which often require extensive parameter tuning for different engine components and lighting conditions.

The performance metrics of our YOLOv8 model also compete favourably with previous deep learning approaches. For example, Li et al., 2023 reported a mAP of 96.1% for their enhanced YOLOv7 implementation, whereas our system achieves 98.9% at IoU threshold 0.5. This improvement can be attributed to the architectural advancements in YOLOv8, particularly its enhanced feature extraction capabilities and more efficient neck structure. Similarly, while Brandoli et al., 2021 achieved 93% precision in corrosion detection, our system maintains perfect precision specifically for crack detection, highlighting the benefits of our targeted training approach and data preparation strategy.

The F1 score of 0.933 achieved by our system exceeds the performance reported by Shen et al., 2019 in their FCN implementation for damage identification in borescope images. This improvement suggests that the object detection framework of YOLOv8 provides advantages over segmentation-based approaches when identifying localised defects such as cracks. Additionally, the absence of false positives in our system addresses a common limitation in previous models, including those reported by Cha et al., 2017, where false positives often occurred in areas with texture patterns similar to cracks.

In terms of processing efficiency, our system exhibits superior performance compared to two-stage detectors such as the Mask R-CNN approach proposed by Shang et al., 2022. The single-stage detection architecture of YOLOv8 enables real-time processing of inspection images, fulfilling the fifth objective of developing a resource-efficient application suitable for deployment on standard maintenance equipment. This efficiency does not come at the cost of accuracy, as evidenced by the high mAP values across different IoU thresholds.

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4.3 Research Insights and Implications

The findings from this research offer several important insights for aircraft maintenance and safety protocols. First, the high precision and recall values demonstrate that deep learning-based inspection systems can now reach levels of reliability that make them viable alternatives to traditional manual inspection processes. The perfect specificity (1.000) achieved by our model suggests that maintenance workflows could be streamlined by focusing human expertise on verifying positive detections rather than conducting exhaustive manual examinations of all components.

The model's robust performance across various crack morphologies and surface conditions, as shown in Figure 4, indicates that the system can handle the visual variability inherent in real-world borescope inspections. This capability directly addresses the first research objective of designing a YOLOv8 architecture optimised for the challenging visual environment of borescope inspections. The consistent detection across different lighting conditions and surface textures suggests that the data augmentation techniques and transfer learning methodologies implemented have successfully enhanced the model's generalisation capabilities, fulfilling the second research objective.

The quantitative evaluation presented in Table 1 and Figures 2-3 fulfils the third research objective by providing a rigorous assessment of the system's performance. The high mAP values at different IoU thresholds demonstrate that the model not only detects the presence of cracks but also accurately localises them within the inspection images. This precise localisation capability enables more targeted maintenance interventions, potentially reducing repair times and costs.

The practical implementation of the detection system as a Windows application, shown in Figure 5, addresses the fifth research objective of developing user-friendly software for deployment in maintenance workflows. The integration of capture and upload functionalities ensures compatibility with existing borescope hardware, making the transition to AI-assisted inspection more accessible for maintenance teams.

From a broader perspective, this research contributes to the advancement of predictive maintenance in aviation. The ability to detect cracks with high accuracy and efficiency enables earlier identification of potential failures, thereby extending component lifespans and enhancing overall aircraft safety. The reduction in false negatives compared to manual inspection methods could significantly decrease the risk of undetected defects leading to in-service failures.

The practical implications of this research extend beyond immediate maintenance applications. The methodology developed could be adapted for other inspection scenarios in aviation and adjacent industries where visual detection of surface defects is critical. Furthermore, the successful implementation of YOLOv8 for this specific application provides a blueprint for developing similar systems for detecting other types of defects in aircraft engines, potentially creating a comprehensive suite of AI-assisted inspection tools for aviation maintenance.

5.0 Conclusion and Recommendations

5.1 Conclusion

This research has successfully developed and validated a YOLOv8-based deep learning system for detecting and classifying microcracks in aircraft jet engine components. The implementation achieved exceptional performance metrics including perfect precision (1.000), high recall (0.875), perfect specificity (1.000), and an overall accuracy of 0.909, positioning it as a significant advancement for aircraft maintenance protocols. Training progression analysis revealed optimal generalisation capabilities with consistent convergence of loss curves without overfitting. Comparative analysis demonstrated clear advantages over traditional computer vision techniques and previous deep learning approaches, with higher mAP values and better precision-recall characteristics. The integration of the trained model into a user-friendly Windows application represents the practical culmination of this research, providing maintenance personnel with an accessible tool that seamlessly incorporates into existing borescope inspection workflows. This research makes a substantive contribution to aircraft maintenance practices by providing a reliable, efficient means of detecting potential component failures before they progress to critical stages.

5.2 Recommendations

The datasets should be extended to capture more defect types, including corrosion, erosion, and impact of damage. Also, the model should be tested with scalable datasets to evaluate detection performance. Future iterations should implement temporal analysis capabilities for tracking defect progression across consecutive inspections, enabling quantitative assessment of growth rates and supporting informed maintenance planning. Finally, comprehensive validation studies should be conducted in collaboration with aviation regulatory authorities to establish formal acceptance of AI-assisted inspection methods as part of certified maintenance procedures.

5.3 Research Limitations

Despite significant advancements in automated crack detection, several limitations should be acknowledged. The training and validation datasets represent a limited subset of possible defect presentations and engine component types, necessitating more extensive datasets for comprehensive real-world deployment. Performance variations may occur when implemented with different borescope equipment configurations, potentially affecting detection accuracy. The current implementation focuses on binary classification without addressing defect severity categorization or dimensional analysis, constraining the system's utility for nuanced maintenance decisions.

While designed for standard maintenance equipment, optimal performance may require specific hardware configurations, limiting immediate deployment across all facilities. The single false negative identified in testing highlights a persistent risk that requires further refinement to address specific visual conditions contributing to missed detections. Finally, the system has not been comprehensively tested across the full range of environmental conditions encountered in aircraft maintenance facilities, including extreme lighting variations and access scenarios that may impact image quality.

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