AI-Driven Aircraft Maintenance System for Real- Time Crack Detection and Predictive Maintenance

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Abstract - This paper proposes the development of an advanced AI-driven aircraft maintenance system designed to address critical inefficiencies in traditional maintenance practices. The system integrates multiple deep learning and machine learning models to enhance predictive capabilities. YOLO (You Only Look Once) is employed for real-time crack detection in aircraft structures, offering rapid and accurate identification of structural damage. Machine learning algorithms are utilized to estimate battery life, incorporating real-world data such as charge/discharge cycles and environmental conditions. Additionally, predictive models analyze sensor data from jet engines to forecast their remaining useful life (RUL), allowing for timely interventions. By combining these functionalities into a centralized platform, the proposed system enables proactive maintenance, reduces downtime, enhances safety, and lowers operational costs. This integrated approach transforms conventional reactive and schedule-based maintenance into a dynamic, data-driven framework. The real-time insights and personalized predictions provided by the system empower maintenance teams to address potential failures before they occur, ensuring optimized maintenance schedules and improved operational reliability. By leveraging cutting-edge AI technologies, this research has the potential to revolutionize aircraft maintenance practices, delivering significant advancements in safety, efficiency, and cost-effectiveness within the aviation industry.

I INTRODUCTION

Aircraft maintenance is a critical aspect of aviation safety and efficiency, yet traditional practices often fail to address the challenges posed by modern operational demands. Current maintenance methods rely heavily on scheduled inspections and reactive repairs, which lead to unnecessary downtime, increased operational costs, and potential safety risks. Crack detection, for instance, is typically conducted manually through visual inspections, which are time-consuming, labor- intensive, and prone to human error. Such limitations compromise the reliability of aircraft and increase the likelihood of undetected structural damage. Similarly, battery life estimation in aircraft systems remains inadequate. Most estimates are based on manufacturer guidelines, which do not account for real-world variations in usage, environmental conditions, and degradation patterns. This results in premature battery replacements or unexpected failures, further impacting operational reliability. In jet engines, life cycle estimations are often derived from historical averages, failing to consider individual usage patterns or sensor-based real-time data, which can lead to unexpected breakdowns and costly repairs. The absence of an integrated, data-driven approach to address these challenges highlights the need for advanced solutions. Without real-time monitoring and predictive capabilities, airlines face significant operational inefficiencies, escalating costs, and compromised safety. The lack of proactive measures to identify potential failures underscores the importance of developing a smarter, AI- driven maintenance framework.

II LITERATURE SURVEY

[1]. The study emphasized how this technology minimizes human error while ensuring structural integrity and demonstrated the capability of YOLO in detecting cracks with exceptional accuracy and speed, significantly reducing the time and effort required for manual inspections. [2]. Machine learning enhances predictive maintenance for aircraft engines by analyzing sensor data to predict health and detect anomalies, reducing downtime and costs. These advancements improve reliability, optimize maintenance schedules, and boost operational efficiency. [3]. Deep learning enhances battery life estimation for aircraft by analyzing charge cycles, environmental conditions, and usage patterns for precise predictions. Advanced models enable real-time insights, ensuring timely replacements and improved reliability. [4]. Integrating AI technologies, such as computer vision for crack detection and predictive analytics for battery and engine maintenance, enhances aircraft maintenance efficiency. AI-driven frameworks streamline operations, reduce costs, and improve safety through a unified management approach. [5]. AI-powered real-time monitoring systems enhance aircraft maintenance by analyzing sensor data to predict failures and provide early alerts. Integrating predictive analytics improves safety, efficiency, and cost reduction, enabling proactive maintenance strategies. [6]. This paper proposes a method for

identifying and evaluating aircraft skin damage using UAV images, GLCM, and a cloud model. The model is effective but requires further optimization to reduce errors and improve accuracy for broader damage assessment [7]. The study highlights AI- driven predictive maintenance (PdM) in manufacturing, leveraging ML and DL models to enhance reliability, reduce costs, and optimize asset utilization. While AI improves failure prediction accuracy and reduces downtime, challenges like data quality, high costs, and model interpretability must be addressed for broader adoption. Future advancements include hybrid AI models, explainable AI, edge computing, and AI-as-a-Service, driving Industry 4.0 transformation. [8]. The integration of AI in aircraft maintenance enhances predictive capabilities, efficiency, and sustainability. By leveraging AI-driven practices and KPIs, the aviation industry can optimize operations, ensuring long-term competitiveness and operational excellence. [9]. The study explores future trends in AI-based predictive maintenance (PdM), including big data analytics, autonomous maintenance, zero-touch operations, blockchain for security, and reinforcement learning for continuous improvement. AI-driven PdM enhances efficiency, cost savings, and safety, with explainable AI ensuring trust. Future advancements, including generative AI, will further improve machine autonomy and adaptability in dynamic environments. [10]. The study highlights the growing role of Industry 4.0 technologies like AR, additive manufacturing, and machine learning in aircraft maintenance, though most remain in the pre-production stage. Successful implementation depends on investment and regulatory adaptation, with collaboration among governments, industry, and researchers essential for realizing their full potential in improving efficiency, cost- effectiveness, and sustainability. [11]. AI-driven predictive maintenance in aviation utilizes machine learning, IoT, and data analytics to monitor aircraft components, predicting failures before they occur. This proactive approach enhances safety, reduces downtime, and lowers maintenance costs, transforming aircraft operations for greater efficiency. [12]. The paragraph presents a layered detection strategy using digital image processing to enhance crack detection in aircraft structures by improving accuracy and reducing interference. It also explores strain data analysis for early detection and suggests applications in aircraft endurance testing. [13]. The paragraph discusses evaluating crack detection models on realistic datasets with complex backgrounds, highlighting the YOLOv10x model for its superior accuracy and inference speed. It emphasizes transfer learning for improved detection precision, potential applications in asphalt pavement monitoring, and future optimizations like model pruning, quantization, and lightweight architectures for efficient deployment on edge and GPU devices. [14]. The passage evaluates AI-driven predictive maintenance in aerospace, addressing scalability, security, and compatibility challenges while highlighting edge computing and adaptive algorithms. It recommends further research on AI adaptation, blockchain security, and human-AI interaction, along with quantum computing and ethical frameworks for improved integration. [15]. This paper proposes an Autoencoder-based Deep Belief Network (AE-DBN) for Remaining Useful Life (RUL) prediction of aircraft engines, demonstrating superior performance over standard DBN and other DL models using RMSE, MAE, R^2, and Score metrics. Experimental results show that AE-DBN outperforms state-of-the-art methods on multiple datasets. Future work includes swarm-based optimization for hyperparameter tuning and hybridizing with other DL models to enhance accuracy and efficiency. [16]. The conclusion emphasizes AI's primary role in aircraft engine maintenance, the importance of the C-MAPSS dataset, necessary support systems, and LSTM's effectiveness in time- series predictions. Future research should focus on specific components and use industry-relevant data for better applicability. [17]. This paper reviews novel solutions in Predictive Maintenance (PdM), highlighting its potential to optimize aircraft component lifespan and reduce costs through AI and automation. Future research should focus on automated PdM tools using AI and Auto-ML to improve accessibility, industry adoption, and operational efficiency. [18]. Recent advancements in artificial intelligence (AI) and predictive analytics have significantly improved aircraft maintenance and system management, proposed a deep learning-based approach for predictive analytics in aircraft battery management. [19]. Developed a comprehensive AI- driven framework for optimizing aircraft maintenance, as detailed in the Journal of Aircraft. Their research integrated machine learning techniques with maintenance scheduling strategies, focusing on reducing downtime and improving aircraft reliability. [20]. Explored real-time monitoring and predictive maintenance for aircraft systems using AI in Aerospace Computing and Engineering. Their study highlighted the role of AI in analyzing real-time sensor data to predict potential system failures.

III METHODOLOGY

The method for crack detection is, the system utilizes the YOLO (You Only Look Once) model, which processes entire images in a single pass, enabling real-time detection of structural cracks in aircraft components. The model is fine-tuned using transfer learning on an aircraft-specific dataset containing high-resolution images with annotated cracks. To improve robustness, data augmentation techniques such as image rotation, flipping, brightness adjustment, and noise addition are applied. The detection process follows a regression-based approach, where bounding box coordinates and confidence scores are optimized to ensure accurate identification of cracks while minimizing false positives and negatives.

YOLO formulates object detection as a regression problem:

$$\hat{P}(C) = \Sigma_{\mathrm{i}=1}^{s^2} 1_{ij}^{obj} \left((x - x_i)^2 + (y - y_i)^2 + \left(\sqrt{w} - \sqrt{w_i}\right)^2 + \left(\sqrt{h} - \sqrt{h_i}\right)^2 \right) + \lambda_{obj} \Sigma_{\mathrm{i}=1}^{s^2} 1_{ij}^{obj} \left(C_i - \hat{C}_i\right)^2$$

where,

- x, y, w, h are the bounding box coordinates
- C is the confidence score
- s^2 represents grid cell
- λ_{obj} is the weight for bounding box loss

For battery life estimation, multiple machine learning models, including Random Forest, Gradient Boosting, and Neural Networks, are explored. These models analyze key features such as charge-discharge cycles, voltage levels, current flow, temperature, and humidity to predict the Remaining Useful Life (RUL) of batteries. The estimation process is formulated as a regression problem, where hyperparameter tuning using Grid Search and Bayesian Optimization enhances model performance. Metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used to evaluate accuracy, ensuring reliable predictions under diverse operational conditions.

The battery degradation function is modeled as:

$$RUL = f(V, I, T, C) + \epsilon$$

where,

- RUL is remaining Useful Life of the battery
- V is voltage
- I is current
- T is temperature
- C is charge cycles
- ϵ is random noise/error term

Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\Sigma_{i=1}^{n}(y - \hat{y}_i)^2$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\Sigma_{i=1}^{n}|y_i - \hat{y}_i|$$

In jet engine predictive maintenance, Long Short-Term Memory (LSTM) networks are employed to analyze time-series sensor data, including vibration intensity, pressure levels, and temperature gradients. LSTMs capture sequential dependencies in sensor readings to forecast engine degradation and predict failures before they occur. The model is trained using sensor data labeled with RUL values, optimizing its performance through backpropagation. Additionally, statistical models like ARIMA are used for benchmarking, while ensemble techniques such as stacking and voting enhance predictive accuracy. The effectiveness of the system is validated using regression metrics like MSE and R-Squared, ensuring that predictions generalize well across different aircraft engines.

The hidden state update equation in LSTM:

$$h_t = \sigma(W_x x_t + W_h h_{t-1} + b)$$

where,

- x_t is the input at time step t
- h_t is the hidden state
- W_x, W_h are weight matrices
- b is the bias term

The predicted Remaining Useful Life (RUL) is computed as:

$$RUL_t = W_{out} h_t + b_{out}$$

where,

- W_{out} , b_{out} are the output weight and bias
- The model is trained using MSE loss

By integrating these AI-driven approaches into a centralized maintenance platform, the system enables proactive interventions, minimizing downtime and reducing operational costs. The combination of real-time crack detection, battery health estimation, and jet engine predictive maintenance transforms conventional schedule-based maintenance into a dynamic, data-driven framework. This enhances, optimizes maintenance schedules, and significantly improves operational reliability within the aviation industry.

IV MODEL SELECTION

YOLO is selected for crack detection due to its speed and accuracy. YOLO processes entire images in a single pass, making it ideal for real-time inspections. The model is pre trained on general object detection datasets and fine-tuned using transfer learning on the aircraft-specific crack dataset. This ensures that the model adapts to the unique characteristics of aircraft structures.

For battery life estimation, multiple machine learning models are explored, including Random Forest is known for its robustness against overfitting and ability to handle complex feature interactions. Gradient Boosting is effective for achieving high accuracy through iterative refinement of wealearners. Neural Networks is used to capture non-linear relationships between features and predict degradation patterns. Hyperparameter tuning is performed using techniques like grid search and Bayesian optimization to optimize model performance.

Long Short-Term Memory (LSTM) networks are employed for jet engine predictive maintenance due to their ability to analyze sequential data and capture temporal dependencies. These models are trained on time-series sensor data to predict the remaining useful life (RUL) of engines. Statistical models, such as ARIMA, are also used for benchmarking. Ensemble techniques, such as stacking and voting, are explored to combine the strengths of multiple models and enhance overall performance.

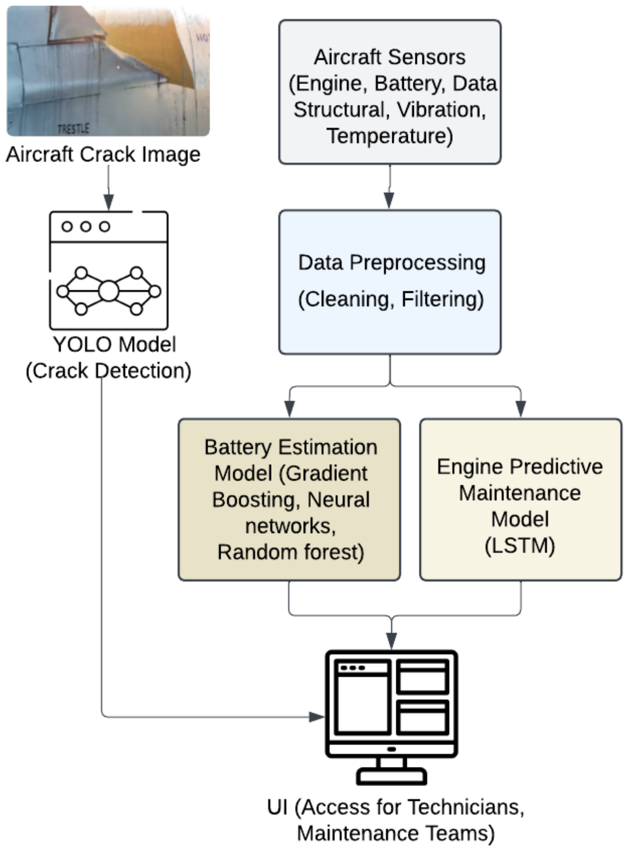

Fig. 1. System workflow

V DATASET DESCRIPTION

The datasets utilized in this study form the foundation for training, testing, and validating the AI models. Each dataset is specifically tailored to its corresponding maintenance task: crack detection, battery life estimation, and jet engine predictive maintenance.

The crack detection dataset consists of thousands of high-resolution images of aircraft structures. These images capture different sections of the fuselage, wings, and other critical components under varying conditions, including changes in lighting, material textures, and environmental factors. To ensure the dataset is representative, images are sourced from a combination of publicly available datasets, proprietary repositories, and industry collaborators. Each image in the dataset is annotated with bounding boxes that highlight cracks, specifying their size, shape, and orientation. To increase dataset diversity and improve the model's robustness, data augmentation techniques are applied. These include image rotation, flipping, brightness adjustments, noise addition, and scaling. Such preprocessing ensures the dataset covers the wide range of scenarios encountered in real-world inspections.

The dataset for battery life estimation comprises time-series data capturing multiple variables, including charge-discharge cycles, voltage levels, current flow, temperature, and humidity. These datasets are collected over extended periods to capture the complete lifecycle of batteries, from their initial deployment to end-of-life. To account for diverse operating conditions, data is gathered from aircraft operating in different climates, altitudes, and usage scenarios. The dataset also includes metadata such as battery type, manufacturer specifications, and historical performance logs. This comprehensive approach ensures that the models trained on this data can generalize across different battery types and operational conditions.

For jet engines, the dataset integrates real-time sensor readings with historical maintenance records. Key sensor parameters include vibration intensity, pressure levels, temperature gradients, and rotational speeds. The dataset also incorporates failure records and repair logs, providing context for how specific patterns in sensor data correlate with engine performance degradation. To enhance the dataset's value, anomaly detection methods are used to identify and isolate events indicative of impending failures. Additionally, data is segmented into training, validation, and testing subsets, ensuring rigorous evaluation of the predictive maintenance models.

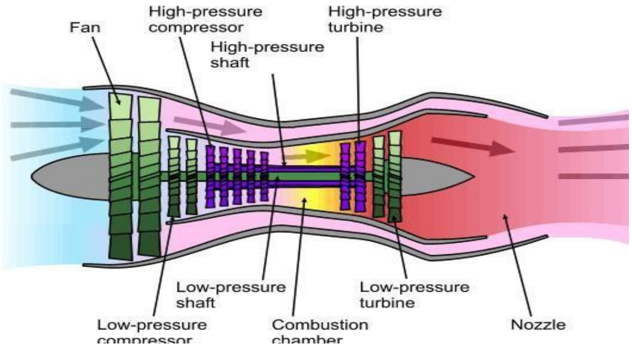

Fig. 2. Jet Engine Internal Structure

This figure depicts the internal structure of a jet engine, labeling key components such as the fan, compressors, turbines, and combustion chamber. Jet engine predictive maintenance relies on analyzing time-series data from sensors placed at various components. Parameters like vibration, pressure, and temperature are monitored to estimate the remaining useful life (RUL) of critical engine parts.

VI DATA COLLECTION

For crack detection, high-resolution images are captured during routine aircraft inspections. Drones equipped with advanced imaging sensors, such as high-definition and infrared cameras, are deployed to capture detailed visuals of aircraft surfaces. These drones can access hard-to-reach areas, ensuring comprehensive coverage of the aircraft. Human inspectors also use handheld devices to capture close-up images of suspected damage areas. To ensure high-quality annotations, manual labeling is performed by experts who delineate cracks and categorize them based on severity and type (e.g., hairline cracks, deep fractures). This annotated data serves as ground truth for training the crack detection model.

Data for battery life estimation is collected through onboard monitoring systems integrated into aircraft electrical systems. These systems track variables like charge-discharge cycles, voltage fluctuations, and temperature variations in real time. Data is transmitted to a central repository, where it is aggregated and analyzed. To capture a comprehensive picture of battery performance, data from multiple aircraft operating under different conditions is collected. This ensures that the dataset accounts for variations in battery degradation due to environmental factors, usage intensity and operational settings.

Jet engine maintenance data is collected using embedded sensors that continuously monitor engine parameters. These sensors generate real-time data streams, capturing metrics such as vibration levels, pressure readings, and temperature changes during engine operation. The data is supplemented with historical maintenance logs, which provide details about past repairs, part replacements, and failure events. Field data is also collected from operational aircraft to validate the models under real-world conditions. This ensures that the predictive maintenance system performs reliably across various operational contexts.

VII DATA PREPROCESSING

Images for crack detection undergo several preprocessing steps to improve their quality and ensure they are suitable for model training. These steps includes, Resizing where images are resized to uniform dimensions to standardize input for the YOLO model. Contrast Enhancement Techniques such as histogram equalization are applied to improve visibility in poorly lit areas. Noise Reduction Filters, such as Gaussian blur, are used to remove noise and enhance image clarity. Normalization pixel values are normalized to a consistent range, ensuring stable training performance.

Battery life data is preprocessed to clean and standardize the time-series data. Key steps include Handling Missing Data where missing values are imputed using methods like linear interpolation or forward filling. Outlier Detection Extreme values are identified and removed using statistical methods such as the Z-score or interquartile range (IQR). Feature Engineering serived features, such as charge discharge efficiency, temperature sensitivity, and cumulative degradation, are computed to enhance the model's understanding of battery performance. Scaling: Data is scaled using normalization or standardization to ensure compatibility across different sensors. Long Short-Term Memory (LSTM) networks are employed for jet engine predictive maintenance due to their ability to analyze sequential data and capture temporal dependencies. These models are trained on time-series sensor data to predict the remaining useful life (RUL) of engines. Statistical models, such as ARIMA, are also used for benchmarking. Ensemble techniques, such as stacking and voting, are explored to combine the strengths of multiple models and enhance overall performance.

VIII RESULT AND DEISCUSSION

The table provides a detailed overview of the performance metrics achieved for the three core components of the system: Crack Detection, Battery Life Estimation, and Jet Engine Predictive Maintenance. These metrics are essential in evaluating the effectiveness and reliability of the AI models used in the system.

For crack detection, metrics such as precision, recall, and F1-score highlight the model's ability to accurately identify structural cracks while minimizing false positives and negatives. The inference time demonstrates the system's real-time detection capabilities, ensuring prompt responses during inspections.

Battery life estimation is evaluated using regression metrics like Mean Squared Error (MSE), R-Squared, and Mean Absolute Error (MAE), reflecting the model's accuracy in predicting the remaining useful life of batteries under varying operational conditions.

Jet engine predictive maintenance focuses on regression analysis as well, utilizing MSE, R-Squared, and MAE to assess the system's ability to predict the remaining useful life (RUL) of engine components. These metrics emphasize the model's capability to generalize across diverse datasets and operational scenarios.

Together, these performance metrics validate the robustness and practical applicability of the system, ensuring it meets the demands of real-world aviation maintenance tasks.

TASK	Crack Detectio n	Batter y Life Estimation	Jet Engine Predictive Maintenanc e
Precisio n (%)	94.8	-	-
Recall (%)	92.3	-	-
F1-Scor e (%)	93.5	-	-
Inferenc e Time (s)	0.015	-	-
MSE	-	2.78	5.12
R-Squared	-	91.4	88.7
MAE (cycle)	-	1.43	2.31

Table 1. Performance Metrics

The loss graph observed during model training. The graph shows the loss value decreasing over epochs, indicating successful optimization of the model. The crack detection model and other AI modules were trained using supervised learning. The loss function measures the difference between predicted and actual values, and its consistent reduction across epochs signifies improved model accuracy.

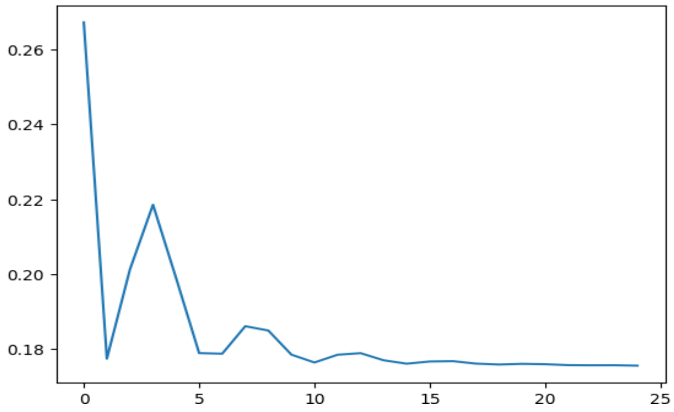

Fig. 3. Loss Graph during Model Training

This graph compares the performance metrics (e.g., accuracy, precision, recall, and F1 score) of the models used for crack detection, battery life estimation, and jet engine predictive maintenance.
X-axis: Models (e.g., YOLO, Random Forest, LSTM)
Y-axis: Performance Metrics (e.g., percentage or score)
To demonstrate the effectiveness of the selected models and highlight the best-performing model for each task.

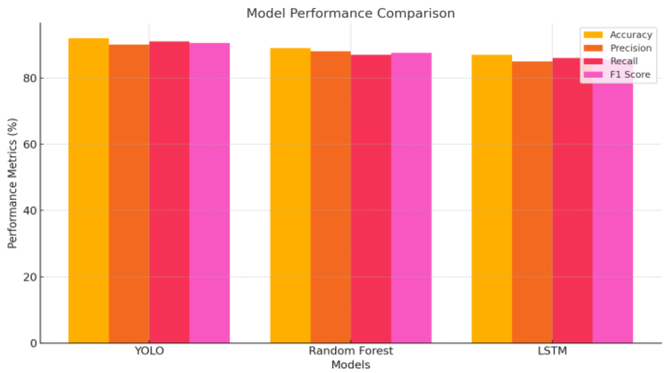

Fig. 4. Model Performance Comparison

This graph shows the prediction accuracy of the AI system over multiple iterations or training epochs for tasks such as crack detection, battery life estimation, and jet engine lifespan prediction.
X-axis: Time (e.g., epochs or iterations)
Y-axis: Prediction Accuracy (e.g., percentage)
To illustrate how the model's accuracy improves during training and to validate the system's reliability over time.

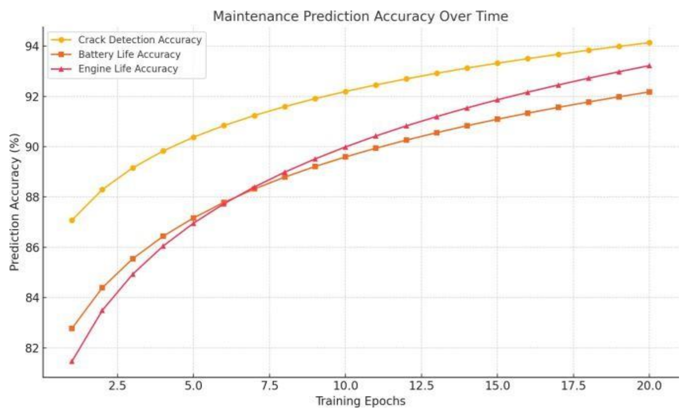

Fig. 5. Maintenance Prediction Accuracy

IX CHALLENGES ENCOUNTERED

One of the primary challenges was obtaining high-quality datasets that represent real-world scenarios. While publicly available datasets exist, they often lack diversity in terms of environmental conditions, material types, and structural configurations. For instance, datasets for crack detection may not include images captured under low-light or extreme weather conditions, limiting the model's ability to generalize. Additionally, missing or noisy data in battery and jet engine datasets required extensive preprocessing to ensure reliability.

Training deep learning models such as YOLO and LSTM for high-dimensional datasets required significant computational resources. The complexity of processing large volumes of image and time-series data posed challenges in terms of memory usage, training time, and hardware requirements. This necessitated the use of advanced hardware accelerators, such as GPUs, and optimization techniques to reduce computational overhead.

Combining different AI models for crack detection, battery life estimation, and engine predictive maintenance into a single, integrated platform was another major challenge. Each model has unique input requirements, output formats, and computational needs, which made integration complex. Developing a centralized system that ensures seamless communication between the models while maintaining accuracy and efficiency required extensive effort.

Testing and validating the system under real-world operational conditions presented logistical and technical difficulties. Field deployments required collaboration with industry partners, access to operational aircraft, and adherence to strict safety protocols. Ensuring that the system performed reliably across diverse conditions was a time- consuming and resource-intensive process.

X LIMITATION

While the system achieves high accuracy and reliability, certain limitations remain. The dependency on high-quality datasets and advanced hardware may limit accessibility for smaller operators. Future research should focus on developing lightweight models and exploring transfer learning to adapt the system for resource-constrained environments. Additionally, real-world validation over extended periods is necessary to refine the system’s performance further.
Moreover, the system's reliance on high-quality datasets presents a significant challenge, as acquiring diverse, well-labeled data can be costly and time-consuming. In cases where data is biased or insufficient, the model’s generalization capability may be compromised, leading to reduced accuracy in real-world applications. Ensuring data quality requires continuous updates and refinements, adding to the overall complexity of system maintenance. Additionally, the system's dependence on advanced hardware, such as high-performance GPUs or specialized processors, increases computational costs and energy consumption. This creates a barrier for smaller organizations with limited resources, restricting accessibility and adoption in resource-constrained environments.

Another limitation is the system’s potential latency issues when handling real-time processing tasks, particularly in large-scale implementations. High computational demands may slow down response times, affecting user experience and decision-making efficiency. Furthermore, the model's adaptability across different domains remains a challenge, as extensive fine-tuning and retraining are often required when deploying the system in new environments. This limits its scalability and flexibility, making widespread implementation more difficult.

To address these limitations, future research should explore techniques such as model compression, edge computing, and transfer learning to enhance computational efficiency and reduce hardware dependency. Developing lightweight models that require less processing power while maintaining accuracy can improve accessibility for smaller operators. Additionally, long-term real-world testing is crucial to refining performance, identifying potential weaknesses, and ensuring the system remains robust and reliable across diverse applications and operational conditions.

XI CONCLUSION

The proposed AI-driven aircraft maintenance system demonstrates the potential to revolutionize maintenance practices in the aviation industry. By integrating YOLO for real-time crack detection, machine learning models for battery life estimation, and predictive maintenance algorithms for jet engines, the system addresses key limitations of traditional maintenance methods. The comprehensive approach ensures enhanced safety, reduced downtime, and significant cost savings by enabling proactive and data-driven maintenance decisions. This research contributes to the growing body of knowledge on AI applications in aviation by combining advanced technologies into a unified platform. The findings underscore the importance of leveraging diverse datasets, optimizing model performance, and integrating multi-modal systems to achieve practical, scalable solutions. Despite the challenges encountered, the system provides a robust foundation for future innovations in aircraft maintenance.

The results of this research highlight the transformative impact of AI on aircraft maintenance, showcasing how real- time monitoring and predictive capabilities can significantly improve operational efficiency. The study's integration of multiple AI models is a step forward in addressing the fragmented nature of traditional maintenance practices, offering a centralized solution that combines crack detection, battery management, and engine monitoring.

The system’s ability to predict potential failures and recommend timely interventions has significant implications for the aviation industry. Airlines can optimize maintenance schedules, minimize unplanned downtime, and improve safety by relying on data-driven insights. Additionally, the cost savings associated with reducing unnecessary replacements and repairs make the system an economically viable option for widespread adoption.

One of the strengths of the proposed system is its scalability and adaptability. The modular architecture allows it to be customized for different aircraft models and operational contexts. For example, additional sensors or data sources can be incorporated to enhance the system's capabilities without requiring a complete redesign.
While the system achieves high accuracy and reliability, certain limitations remain. The dependency on high-quality datasets and advanced hardware may limit accessibility for smaller

operators. Future research should focus on developing lightweight models and exploring transfer learning to adapt the system for resource-constrained environments. Additionally, real-world validation over extended periods is necessary to refine the system's performance further. As AI systems become integral to critical industries like aviation, ethical and regulatory concerns must be addressed. Ensuring data privacy, maintaining transparency in decision- making processes, and adhering to safety standards are essential for building trust and ensuring compliance with industry regulations.

In summary, the proposed system represents a significant advancement in aircraft maintenance, demonstrating the potential of AI to enhance safety, efficiency, and cost effectiveness. Continued research and development will pave the way for broader adoption and further innovations in this critical field.

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