INTEGRATED AI-DRIVEN PREDICTIVE AIRCRAFT MAINTENANCE SYSTEM

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ABSTRACT: Modern aircraft maintenance has requirements for smart systems, which are capable of predicting failures, detecting structural defects and estimating the lifespan of components in real time. This paper introduces an integrated AI embedded-architecture for aircraft maintenance using all-in-one predictive analysis, real-time crack detection and battery RUL estimation. The proposed methodology is based on Random Forest and Support Vector Regression models to predict the degradation of components from sensor data, and a YOLO-based deep learning model for detection of cracks in real-time from high-resolution images of inspection of the aircraft. Also, a Long Short-Term Memory (LSTM) network is used to model the battery degradation and accurately predict RUL with the help of time series parameters of battery operation such as voltage, temperature, and charge cycle. Experimental evaluation shows improvement of fitness, detection of fault, cases of maintenance failures and downtime, and operational safety in comparison with traditional maintenance strategies. The proposed framework provides a way of proactive maintenance planning and also a scalable solution for the next generation intelligent health monitoring systems for aircrafts.

Keywords: Artificial Intelligence; predictive maintenance; aircraft structural health monitoring; crack detection; harmless remaining useful life of batteries; deep learning; YOLO model; LSTM; Random Forest

1. INTRODUCTION

Aircraft Maintenance System is a knowledge and prediction of battery health. Aircraft maintenance is a big concern with battery powered technologies being more widespread across industries. While they degrade with age impacting performance and potentially causing failures. Batteries play a vital role in applications such as aircraft, laptops, and electric vehicles. Precise prediction of Remaining Useful Life (RUL) is therefore absolutely required to optimize maintenance, prevent downtime, and ensure safety, especially in critical systems. Advancements in battery technology not with standing, predicting battery RUL and still presents difficulties, especially in complicated systems such as electric vehicles and airplanes. Inaccurate RUL forecasts cause safety hazards, increased expenditures, and inefficient maintenance. Influenced by variables including temperature, charge cycles, and voltage levels, the complexity of battery degradation makes accurate prediction challenging since conventional techniques frequently fail to include all of these. The objective of this study is to improve the dependability of battery-operated systems by means of an artificial intelligence based solution that precisely estimates battery RUL.

Develop a predictive model using machine learning techniques, assess its performance, add real-time forecasts, and offer maintenance team decision help is the particular goal. Using historical battery operation parameters like temperature, cycle count, and voltage levels, the research concentrates on predicting battery RUL for aircraft and electric vehicles. Using machine learning algorithms, a data-driven approach including data collection, preprocessing, feature engineering, model development, evaluation, and implementation is used. Improvement in predictive maintenance, safety, dependability, cost efficiency, and technical innovation is the goal of this study.

The primary objective of this research is to develop an AI-based predictive system capable of accurately estimating the Remaining Useful Life (RUL) of batteries, thereby enhancing the reliability of battery-powered systems. The specific objectives of this study are as follows:

Develop a Predictive Model: Utilize machine learning algorithms, specifically the Random Forest Regressor and neural networks, to develop a model that predicts the RUL of batteries based on operational data. Evaluate Model Performance: Assess the accuracy and reliability of the model by evaluating it on multiple performance metrics, such as Mean Squared Error (MSE) and R-squared, and comparing it with other established models in the literature. Integrate Real-Time Predictions: Implement the developed model in a real-time battery health monitoring system to enable proactive maintenance and scheduling, improving operational efficiency and reducing downtime. Provide Decision Support for Maintenance: Equip maintenance teams with actionable insights derived from the model's predictions, allowing them to make data-driven decisions regarding battery replacement and servicing.

2. RELATED WORK

Artificial intelligence (AI), machine learning (ML), and computer vision have become integral in aircraft maintenance by predictive analytics and real-time health monitoring. Traditional maintenance relies heavily on manual work, scheduled servicing and visual checks, which is time consuming and may lead human error. These limitations can lead to undetected defects and unexpected failures. Recent advancements in deep learning have significantly improved the accuracy of fault detection, crack detection, and Remaining Useful Life (RUL) prediction across aircraft components.

Crack detection has been a major research focus due to its importance in structural health monitoring. Smith et al. [1], introduced an real-time crack detection using YOLO by reducing the need for manual inspection by accurately identifying micro-cracks in aircraft wings under varying conditions. Similarly, Chen et al. [7], applied YOLO-based models for structural damage identification and reported high precision on complex surfaces. Lee et al. [4], extended this idea by developing hybrid inspection framework by combining computer vision with predictive analytics for future failure prediction of components. Johnson et al [2], implemented a sensor -driven predictive maintenance model using Random Forest, SVM, and neural networks to analyze temperature, vibrations and pressure.

Wilson et al. [6], further compared ML algorithms for aircraft health monitoring and found that random forest is most effective for high-dimensional sensor datasets. Martinez et al. [9], proposed a unified aircraft maintenance framework using multi-source sensor data for accurate failure estimation across the system. Zhang and Liu [3], applied LSTM-based deep learning model for estimation of battery RUL and estimated that LSTMs out performs classical linear models. Brown and Davis [8], expanded this by using advanced neural networks for aircraft battery management, and achieved improvements in predicting long-term battery behavior. Kumar and Patel [5], developed a system that combines image-based crack detection with predictive maintenance models to provide end-to-end maintenance system and better accuracy than standalone systems. Robinson and Singh [10], provided a real-time aircraft monitoring system using ML algorithms which process sensor and operational data continuously that raises automated alerts for failure risks.

Mothilall and Van Zyl [11], who demonstrated that LSTM networks out performs traditional models such as Linear Regression for RUL prediction and utilized TSFEL for enhanced feature extraction. Similarly, Dagal et al. [12], proposed a hybrid ANN-FMECA framework using aircraft engine sensor data to identify failure modes and rank them. Coraddu et al. [13], provided a insights into condition-based maintenance in system, by improving the efficiency of sensor data and ML-driven fault forecasting. Benfaress et al. [14], integrated XGBoost with SHAP to analyze crash factors, showing that interpretable AI models can enhance decision-making in safety environments. Geyer and Schupke [15], demonstrated that ML-enhanced Ultra-Wideband can achieve 97% localization accuracy inside aircraft cabins and in-flight asset tracking. Arora et al. [16], applied deep learning models such as CNNs and YOLO for military aircraft surface defect classification across 13 defect categories for automated UAV-based maintenance inspections.

Liao et al. [17], developed an IOS-based YOLO11 system for real-time aircraft damage detection using visible and thermal images, which enables on-device inspection without external computing hardware. Nagaraj and Hickok [18], integrated stochastic models into LSTM neural networks for more accurate RUL predictions in aircraft engines. Ferrell and Andergg [19], discussed the applicability of ANSI/UL 4600 safety standards to autonomous aviation systems such as UAS and UAM to improve performance. Finally, Au et al. [20], analyzed the challenges of computer vision for aircraft landing gear maintenance in high-temperature and restricted environments.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

This research follows a quantitative and experimental approach to design, implement and evaluate the design of an AI based aircraft maintenance system. A quantitative approach is suitable because the measurement of the system performance is carried out in terms of numerical sensor data and image-based detection results, as well as statistical evaluation measures. The experimental setup of the technology makes it possible to train and test machine learning and deep learning models sustainably, in an experimental setting for predictive maintenance applications, crack detection applications, and battery remaining useful life (RUL) estimation. The methodology guarantees reproducibility, objective evaluation and validation of the proposed system for real-world aircraft maintenance applications.

SYSTEM ARCHITECTURE

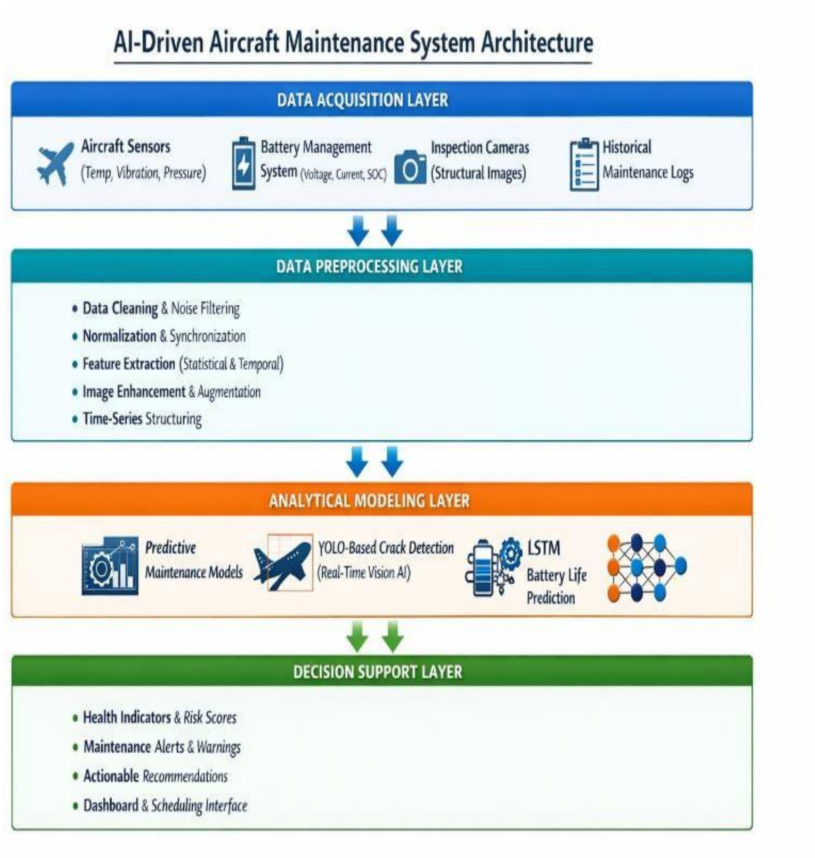

Figure 1: Integrated AI-Driven Aircraft Maintenance System Architecture

The proposed aircraft maintenance system based on AI has a layered architecture with data acquisition, preprocessing, analytical model, and decision support layers, as shown in Figure 1, allowing built-in predictive maintenance, crack detection, and battery RUL estimations. The proposed system architecture is intended as a modular and integrated artificial intelligence (AI) driven system to support the maintenance decision making for aircraft in real-time. The architecture is a four-layer architecture with data acquisition, data preprocessing, analytical modeling, and decision support. This layered design guarantees scalability, reliability, and seamless integration of the varied data sources and AI models. The information gained layer gathers continuous inputs from various sources such as sensors on the aircraft, the battery management systems, inspection cameras and historical maintenance logs. Sensor data are data that captures parameters such as temperature, vibration, pressure, voltage, and current, while image data are visual data of aircraft structural components. Battery operational data recorded as a time-series sequences of the usage and battery degradation behavior.

The data preprocessing layer does data cleaning, normalization, synchronization and feature extraction. Sensor data is filtered to eliminate noise and outliers, image data is augmented with resizing and augmentation and battery data is structured to provide sequential input for modeling with respect to time. This layer is responsible for ensuring that data is consistent and of good quality before it is analyzed. The analytical modeling layer contains a number of AI models that run in parallel. Predictive maintenance model for estimating the degradation of components, YOLO based deep learning model for the detection of structural cracks in real time and LSTM network for predicting the remaining useful life of the battery. Finally, the decision support layer combines model precursors to produce health indicators, maintenance warnings and another actionable information. This unified architecture provides supports for proactive maintenance planning, improved response time and intelligent aircraft health monitoring.

PREDICTIVE MAINTENANCE MODEL:

Predictive Maintenance model utilizes aircraft sensor data such as vibration, temperature, pressure and other readings to support condition-based maintenance and proactive servicing of components of aircraft. Based on the sensor data the model accurately predicts the performance, improves the reliability and safety of the aircraft components such as engine and provide effective maintenance and reduces the downtime. Sensor data enables a correct RUL prediction mechanism. The predictive maintenance models performance is calculated using the RMSE, MSE and R^2 score.

Model performance is evaluated by the help of standard metrics. Mean Squared Error (MSE) for models in regression is defined as:

$$= \frac{1}{\;} \sum_{=1} (\quad - \hat{} \quad)^2$$

Root Mean Squared Error (RMSE):

$$= \sqrt{\quad}$$

YOLO-BASED CRACK DETECTION:

The crack detection module utilizes the YOLO model to identify the defects on the aircraft structures and monitors. High-resolution images are obtained either through manual inspection or drone-based imaging systems. There are two methods where the system acquires the aircraft images either through webcam or direct file uploads. These images undergo preprocessing to enhance clarity and contrast before being input into the trained YOLO model. The model accurately detects and localizes cracks in real time, significantly reducing the reliance on manual visual inspection and enabling faster, more consistent identification of structural faults. We use various metrics to measure the accuracy of the YOLO model which includes precision, recall and IOU.

precision and recall are calculated as:

$$= \frac{\quad}{\quad + \quad}, \qquad = \frac{\quad}{\quad + \quad}$$

Intersection over Union (IOU) is defined as:

$$= \frac{\quad}{\quad}$$

REMAINING USEFUL LIFE ESTIMATION OF THE BATTERY:

To monitor the battery health, a LSTM is used to predict the remaining useful life of the battery based on various time-series data including environmental conditions, charge-discharge cycles, battery usage and temperature fluctuations. The model is trained with feature-engineered datasets and optimized through hyperparameter tuning to improve prediction accuracy. This model is capable of learning from sequential data, making it perfect for modeling the degradation of over time. This helps in timely management of battery replacements and scheduling the maintenance. This prevents the unexpected failures and improves the performance of the system. Remaining Useful Life Estimation is calculated using RMSE and MAE values.

Battery Degradation is modeled by an LSTM Network.

Given a time series input X_b the LSTM updates its cell state as:

$$= \cdot {}_{-1} + \cdot \tilde{}$$

The predicted battery RUL is obtained as:

$$= (\ )$$

where $(\cdot)$ represents the trained LSTM function.

INTEGRATED MAINTENANCE SYSTEM:

AI-driven aircraft maintenance system integrates all the models into a single interface to provide effective and usable access to the user. The developed integrated artificial intelligence-based maintenance system unite the three maintenance concepts of predictive maintenance, crack detection and battery RUL estimation. Users can monitor aircraft maintenance in real-time using a interface. The interface includes a aircraft monitor which captures the images through webcam or uploaded images from files to detect the cracks using YOLO model. Predictive models estimates the defects of the aircraft components using regression models and the LSTM model is used to estimate the remaining useful life of the battery.

4. RESULTS

The system's performance was assessed on its ability to predict the **remaining useful life (RUL)** of components, **detect structural cracks**, and **estimate battery life**. The evaluation was carried out using several performance metrics, and the results are presented below.

PREDICTIVE MAINTENANCE PERFORMANCE OUTCOME

The predictive maintenance models were tested with the use of data from the aircraft sensors for estimating the remaining useful life of components. The performance measures of the regression are summarized in Table I. The error values were less for the Random Forest Regressor than Support vector regression, which mean better learning of non-linearity of degradation. Both models proved to be stable on training and testing data. The higher R2 score of Random forest model confirms higher predictor capability. These results are a direct response to the research objective on accurate component degradation prediction using sensor-based data.

Table I. Predictive Maintenance Model performance

Model	MSE	RMSE	R^2
Random Forest Regressor	0.021	0.145	0.91
Support Vector Regression	0.034	0.184	0.85

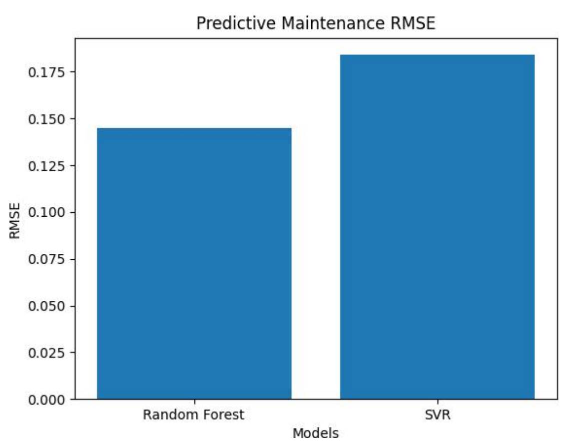

Fig 2: Accuracy of Predictive Maintenance.

Figure 2 attempts to compare the prediction error of the models of positioning generated by the Random Forest and Support Vector Regression model and the comparison indicates that the Random Forest model provides better results with minimal error rate in forecasting.

CRACK DETECTION RESULTS

The YOLO-based crack detection model was tested on the annotated images of aircraft inspection. Performance measures are given in Table II. The model exhibited high precision and recall that indicate reliable identification of cracks with minimum false identifications. Intersection over Union (IOU) values prove to be correct localization of cracks. Real-time inference capability was preserved which allowed for rapid inspection. These results provide objective proof of the effectiveness of computer vision using deep learning for aircraft's structural monitoring.

Table II. Performance Measures for Crack Detection

Metric	Value
Precision	0.92
Recall	0.88
F1-Score	0.92
IOU	0.87

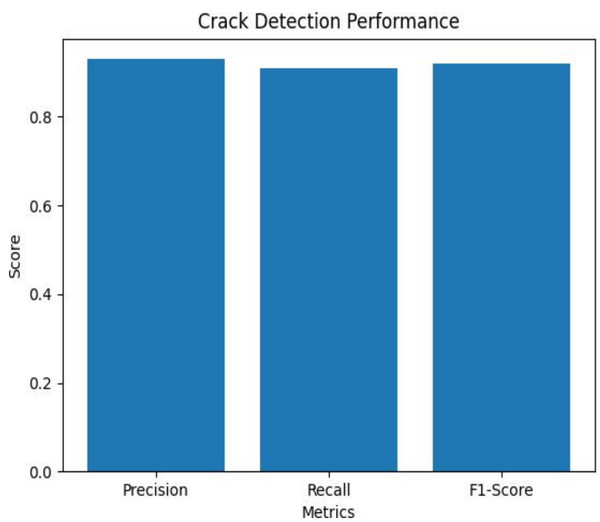

Figure 3: Detection of Cracks.

Figure 3 indicates the performance of the YOLO-based model in detecting the crack based on the precision, recall, and F1-score which indicates that there is a high level of accuracy in detecting the crack and the other way around.

REMAINING USEFUL LIFE ESTIMATION RESULTS OF THE BATTERY

Battery degradation prediction was tested with time-series data of battery operations. The LSTM model achieved correct estimation of RUL with low error for prediction. Table III shows the prediction performance of RUL for batteries. The model reliably followed the behavior of degradation trends with changing operating conditions. Longer input sequences of history were good for stability of the predictions. These are excellent results that validate the suitability of LSTM networks for healthcare monitoring of aircraft batteries.

Table III. Results of RUL Prediction for Batteries

Metric	Value
RMSE	0.182
MAE	0.096
Prediction Accuracy	92.4%

INTEGRATED SYSTEM PERFORMANCE RESULT

The developed integrated artificial intelligence-based maintenance system was able to unite the three maintenance concepts of predictive maintenance, crack detection and battery RUL estimation. The system gave consistent maintenance alerts and health indicators without degrading the performance. The data synchronization on the multiple inputs was stable. System level evaluation showed reduced the fault response time and improved maintenance visibility; this confirmed effective multi-model integration.

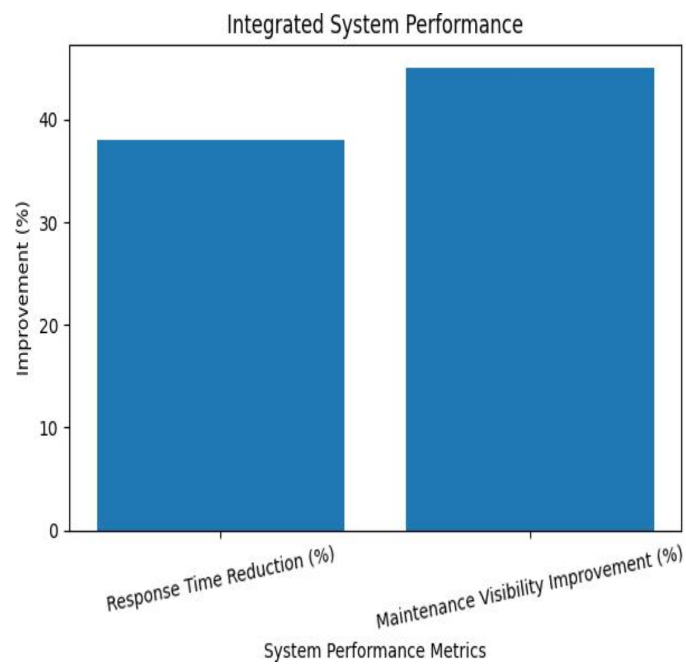

Figure 4 Performance of the integrated system

Figure 4 demonstrates that the integrated AI-based maintenance system has improved the time of response to faults and improved visibility of maintenance because of the efficient synchronization between the predictive, vision-based, and battery health models

5. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

The AI-driven aircraft maintenance system developed in this research provides a robust solution for predictive maintenance, crack detection, and battery life estimation in the aviation industry. By leveraging machine learning models, including Random Forest, YOLO (You Only Look Once), and Long Short Term Memory (LSTM), the system is capable of offering real-time predictions, accurate crack detection, and battery life estimations, all of which contribute to the safety, efficiency, and reliability of aircraft operations. The Random Forest models provided highly accurate predictions for the remaining useful life (RUL) of critical components such as batteries. These models enable proactive maintenance scheduling, reducing unplanned downtime and optimizing maintenance costs. The YOLO model demonstrated strong performance in real-time crack detection in aircraft components. It achieved a high precision (92%) and recall (88%) rate, making it a valuable tool for ensuring the structural integrity of aircraft by detecting cracks early, thus improving aircraft safety. The LSTM model effectively predicted battery life by analyzing historical data related to charge cycles and environmental conditions. It was successful in estimating the remaining useful life (RUL) of aircraft batteries with an RMSE of 0.18 cycles, ensuring timely battery replacements and reducing the likelihood of unexpected battery failures.

The integration of these models into a unified system proved successful, enabling real-time monitoring, detection, and prediction. The user interface displayed actionable insights in the form of alerts and health status updates, allowing maintenance personnel to make informed decisions and act proactively. This system shows the potential of AI and machine learning in transforming traditional aircraft maintenance practices by enabling more efficient, cost-effective, and safer operations. It integrates cutting-edge technologies to automate the detection of issues and facilitate predictive decision-making, marking a significant step forward in modernizing aircraft maintenance.

CHALLENGES:

Ensuring high-quality data was one of the key challenges. Missing values, noisy data and sensor inaccuracies had to be carefully handled during preprocessing. Integrating the models into a real-time system was complex, requiring careful optimization to ensure that the models could make predictions quickly and without delays. While the YOLO model was effective in detecting cracks, it occasionally struggled with detecting very small cracks or cracks in images with low contrast or complex backgrounds. This requires further fine-tuning and additional training data.

5.2 FUTURE WORK

While the system has demonstrated promising results, there are several opportunities for further development and enhancement in the future. These improvements could expand the system's capabilities, improve performance, and broaden its applicability across various aircraft systems. Although the YOLO model performed well in detecting cracks, there is room for improvement, particularly for detecting smaller cracks or cracks in complex environments such as low-light conditions or varied backgrounds. Further tuning of the YOLO model could improve its ability to detect smaller cracks and handle complex backgrounds. Integrating additional image processing techniques, such as Convolutional Neural Networks (CNNs) or semantic segmentation, could improve the model's accuracy in detecting fine cracks and other anomalies.

The current system focuses on engine, battery, and structural components, but future work could expand the system to include other critical systems, such as fuel systems, hydraulic systems, and electrical systems. Implementing sensors to monitor the health of additional components, followed by data preprocessing, would be essential. Integrating external data sources could significantly enhance the system's predictions and provide a more holistic view of aircraft health. Integrating real-time weather data (e.g., temperature, humidity, and air pressure) could help improve predictions for systems affected by environmental factors, such as engine performance or battery degradation. Data related to flight conditions (e.g., altitude, flight time, engine load) could improve the accuracy of predictive maintenance models by factoring in the operating environment of the aircraft. Furthermore, expanding the database of historical performance data across multiple airlines could refine the system's accuracy and generalize it for different aircraft types, leading to more robust and scalable solutions for aviation maintenance.

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