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### Predictive Maintenance of Aircraft Engine Failure

<sup>1</sup> Gaurav Gowda Babu Yashoda, <sup>2</sup> Likith Nagesh, <sup>3</sup> Navaneeth Murthy, <sup>4</sup> Prajwal Tippetwamy, <sup>5</sup> Vignesh Surgani Durgaprasad, <sup>6</sup> Sharadadevi Kaganurmam

<sup>1, 2, 3, 4, 5, 6</sup> Global Academy of Technology (GAT), Bangalore, Karnataka, India

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Corresponding Author: Prajwal Tippetwamy

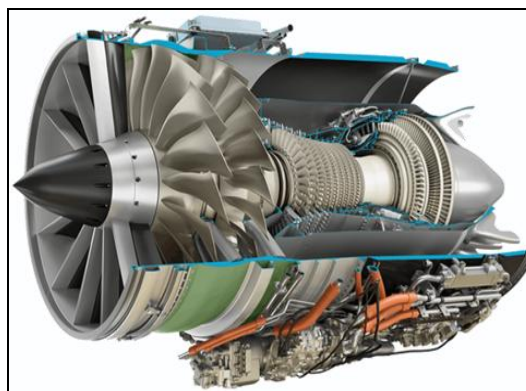
#### Abstract

Imagine if an aircraft component could inform us when it needs replacement or repair. Given the low fault tolerance of aircraft engines, even minor faults can lead to catastrophic outcomes. Thus, accurate and real-time information about engine condition is essential. This can be done through ongoing data gathering, real-time monitoring, and smart analytics. In the aviation industry, predictive maintenance enhances reliability, optimizes the supply chain, and improves operational performance. The primary objective is to ensure engines operate correctly under all conditions, minimizing failure risks. Effective failure prediction methods can significantly enhance maintenance practices.

Data on engine health is primarily gathered during flights, including variables like fan speed, core speed, oil quantity and pressure, fuel flow, and environmental factors such as temperature, aircraft speed, and altitude. Real-time sensor data can model component deterioration. This study investigates the use of LSTM networks to predict maintenance needs in aircraft engines. The LSTM model handles sequential input data, with training conducted on a high-performance processing engine. Combining machines, data, ideas, and people is crucial to understanding the value of predictive maintenance and achieving meaningful business results.

**Keywords:** Predictive Maintenance, Machine Learning Models, Aircraft Engine Failure, Sensor Data Analysis

#### Introduction



The aviation industry has advanced significantly in aircraft maintenance and reliability through cutting-edge technology and data analysis. The availability and functionality of airplane components has always been critical. Accurate failure predictions enhance aircraft system and component availability. Maintaining engine safety and efficiency is crucial in the aviation industry. Maintaining operational engines and promptly identifying potential faults are basic necessities. With the rapid development of Internet of things (IoT) companies can monitor engine components health through sensor data. Systems can be developed to predict component conditions using IoT sensor performance. To full fill missions, components must be preserved or replaced before reaching the end of their useful life. Predicting a component's life state is crucial for industries operating in

fast-paced technological environments. Recent predictive maintenance studies help generate alerts before component failures, enabling effective operation while reducing maintenance costs by preemptively replacing components.

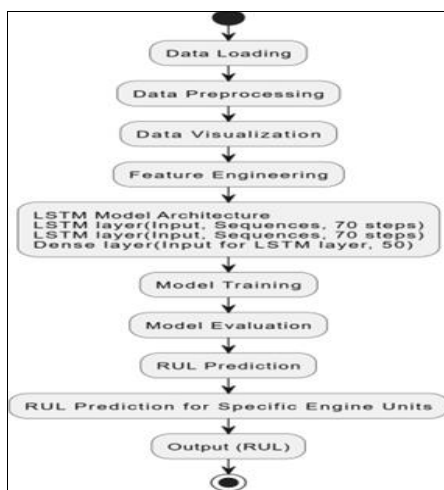
Efficient maintenance extends component life, increases equipment availability, and keeps components in good working condition while reducing costs. The widespread use of sensors facilitates large-scale equipment monitoring data collection, making aircraft engine maintenance prediction feasible. Applying analytics to detect patterns and trends in these data sources can guide maintenance strategies by delivering timely and contextually appropriate information to prevent failures. The data can also highlight areas for possible product design enhancements.

Several strategies exist for determining, preparing, and executing effective maintenance actions for specific assets. The main two maintenance strategies are corrective and preventive. Corrective maintenance has benefits such as maximizing asset lifespan but poses challenges like high spare parts inventory costs, high component latency, overtime labor costs, and poor production availability. Preventive maintenance allows for efficient planning of maintenance operations to ensure readiness and offers clear safety advantages. However, assets are often replaced for safety before reaching their end of life, which is economically inefficient.

As the industry becomes more adept at intelligently monitoring and evaluating equipment to assess repair or replacement needs, there's an opportunity to transition from conventional preventive maintenance to predictive maintenance. This change can significantly lower unplanned downtime, saving millions of dollars, keeping planes operational, and enhancing customer satisfaction.

Main Contributions of This Paper:

- Creation of an LSTM model to forecast aircraft engine maintenance with precise outcome evaluation.



## Literature Survey

Schedule-based maintenance in airlines does not take into account fault predictions in advance, which can lead to unnecessary maintenance when components may have already exceeded their failure thresholds. The growth of industrial IoT data has increased the use of data-driven techniques for predictive maintenance, enabling better decision-making related to safety and efficient maintenance planning. A predictive maintenance model for turbofan engines has been developed to identify key factors for fault

detection and estimate the Remaining Useful Life (RUL) under different operating conditions. Machine learning models, such as Random Forest, have shown to offer more accurate RUL predictions. Moreover, machine learning has also been applied to hydropower systems, where classification algorithms like Support Vector Machines (SVM) and Decision Trees have been found effective in accurately predicting system failures, leading to improved system management.

## Related Work

1. Failure vaticination of aircraft outfit using machine literacy with a mongreal data medication system.
  - This study examines employing machine learning algorithms for forecasting. failures in aircraft equipment through a hybrid data preparation approach. Maintenance and failure Data gathered over a period of two years. identified key input features. The hybrid model employs the Relief algorithm for feature selection and modified K-means clustering to remove noisy data. Algorithms such as Multilayer Perceptron (MLP), support vector regression (SVR) & linear regression (LR) were tested, with LR showing superior prediction accuracy. The model improved predictive maintenance by reliably identifying potential failures, optimizing maintenance schedules, and reducing operational costs.
2. A comprehensive review of deep learning techniques used to detect damage in aero-engine blades.
  - This research evaluates deep learning methods for spotting blade defects, which play a vital role in maintaining aircraft safety. Thirteen primary studies were analyzed, showing convolutional neural networks (CNNs) and models like YOLO and Mask R-CNN frequently used with high accuracy. Challenges include data imbalance, scarcity, and noise sensitivity, along with the lack of standardized benchmarks. The review calls for more advanced learning models and larger datasets to address these limitations.
3. A deep hybrid learning model for detecting rare failures in aircraft predictive maintenance.
  - This research introduces an innovative predictive maintenance model aimed at identifying rare failures. It combines an autoencoder for anomaly detection with a Convolutional Bidirectional Gated Recurrent Unit (BGRU) network for fault prediction. The hybrid model improves rare event identification by learning past and future dependencies, demonstrating enhanced accuracy and reliability over traditional methods.
4. A Digital-Model-Based Approach for Defining HIRF Immunity Design Requirements of Commercial Aircraft Engine Control Systems
  - The paper presents a digital-model-based approach for defining High-Intensity Radiated Field (HIRF) immunity design requirements, modeling engine control system topology and simulating electromagnetic responses. This method estimates induced EM responses and provides tailored HIRF immunity requirements, reducing development costs and enhancing airworthiness certification reliability.
5. Review of High Power and High Voltage Electric Motors for Single-Aisle Regional Aircraft
  - This paper reviews advancements in high-power, high-voltage electric motors for regional aircraft, focusing on

motors in the megawatt range. Challenges include achieving high power density, thermal management, and reliable high-altitude operation. Emerging motor topologies and insulation materials are discussed, emphasizing the need for continued technological evolution to make electric propulsion viable.

6. Analysis of aircraft engine exhaust gas temperature using LSTM models.
  - This study explores predicting Exhaust Gas Temperature (EGT) using LSTM neural networks. EGT is a critical engine health indicator. The LSTM model, trained on real-time in-flight data, showed promising accuracy in predicting future EGT values, improving predictions through batch size adjustments.

### Existing System:

Traditional methods of aircraft engine maintenance typically follow reactive or preventive strategies, without utilizing advanced machine learning techniques for predicting failures.

#### Time-Based Maintenance:

- Maintenance is scheduled based on predefined intervals, regardless of engine health, leading to unnecessary maintenance or missed early failure signs.

#### Condition-Based Monitoring:

- Engines are monitored for specific parameters, with maintenance performed when thresholds are exceeded. However, this system often lacks predictive capabilities, resulting in unscheduled downtime.

#### Manual Inspection & Log-Based Maintenance:

- Relies on manual inspections and logging, prone to human error, and often fails to identify early-stage faults.

### Proposed System:

The proposed system uses machine learning algorithms for predictive maintenance, focusing on evaluating various algorithms for engine failure prediction.

#### Machine Learning Model Comparison:

- The system compares several algorithms to assess their performance in predicting aircraft engine failures based on sensor data. The goal is to identify models that effectively predict Remaining Useful Life (RUL) or

detect early failure indicators.

#### Performance Metrics:

- Models are evaluated based on accuracy, precision, recall, F1-score, mean squared error (MSE), and their ability to generalize and efficiently process data.

#### Feature Engineering & Model Evaluation:

- The impact of feature engineering on model performance is explored, analyzing different data transformations and preprocessing steps to improve prediction accuracy and robustness.

#### Predictive Maintenance Strategy:

- A data-driven, proactive maintenance approach is proposed, moving away from reactive or fixed schedule methods. This strategy enables timely maintenance, optimizing resource allocation, and minimizing unplanned downtime.

### Methodology

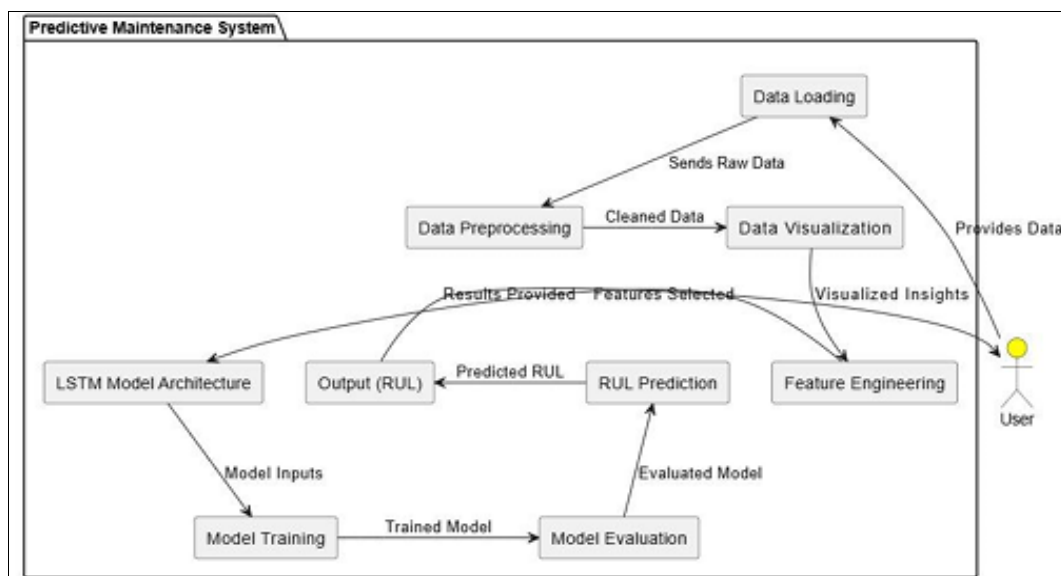
The study utilizes historical engine performance data from sensors, applying machine learning algorithms to identify failure-indicative patterns. Data preprocessing, including cleaning, normalization, and feature extraction, ensures dataset quality and relevance.

### Conclusion

Predictive maintenance stands out as a major advantage of the Industrial Internet of Things (IIoT). Digital tools monitor historical performance and link it to real-time performance, raising alarms for deviations. Advanced analytics determine if variances indicate potential malfunctions, their root causes, and timelines. This approach allows airlines and MROs to preemptively resolve issues, reorganize workflows, and prevent unplanned downtime, enhancing efficiency and cost-effectiveness. Transitioning to predictive maintenance streamlines operations, reduces maintenance-related disruptions, and fosters a digital future for the aviation industry.

### Data Availability

The C-MAPSS dataset can be downloaded from NASA's Center of Excellence Data Repository at: NASA Data Repository.



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