# PREDICTION OF REMAINING LIFETIME OF TURBOFAN ENGINE USING MACHINE LEARNING ALGORITHM

Neetha Das[1], Divya R[2], Gagana R[3], Meghala N[4], V Saanchitha[5]

[1]*Dept of CS&E, Bangalore Institute of Technology, Bangalore, India.*
*E-mail: neethadas@bit-bangalore.edu.in*
[2]*Dept of CS&E, Bangalore Institute of Technology, Bangalore, India.*
*E-mail: 1bi19cs052@bit-bangalore.edu.in*
[3]*Dept of CS&E, Bangalore Institute of Technology, Bangalore, India.*
*E-mail: 1bi19cs056@bit-bangalore.edu.in*
[4]*Dept of CS&E, Bangalore Institute of Technology, Bangalore, India.*
*E-mail: 1bi19cs088@bit-bangalore.edu.in*
[5]*Dept of CS&E, Bangalore Institute of Technology, Bangalore, India.*
*E-mail: 1bi19cs173@bit-bangalore.edu.in*

## ABSTRACT

*Maintenance of equipment is a critical activity for any business involving machines. Predictive maintenance is the method of scheduling maintenance based on the prediction about the failure time of any equipment. The prediction can be done by analyzing the data measurements from the equipment. Machine learning is a technology by which the outcomes can be predicted based on a model prepared by training it on past input data and its output behavior. The model developed can be used to predict machine failure before it actually happens. In this paper, a comparative study of existing set of machine learning algorithm to predict the Remaining Lifetime of aircraft's turbo fan engine is done. The machine learning model were constructed based on the datasets from turbo fan engine data from the Prognostics Data Repository of NASA. Using a training set, a model was constructed and was verified with a test data set. The results obtained were compared with the actual results to calculate the accuracy and the algorithm that results in maximum accuracy is identified.*

**Keyword: -** *Authorization, Predictive Maintenance, Machine Learning*

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## 1. INTRODUCTION

The prediction of remaining lifetime of a turbofan engine is a critical task in the maintenance and operation of aircraft. Machine learning algorithms can be used to analyze sensor data and other factors to predict the remaining useful lifetime of a turbofan engine .The process typically involves several steps, such as data collection, feature extraction, model training, and prediction .Data collection involves gathering sensor data from the engine during its operation. This data can include measurements such as temperature, pressure, vibration, and other parameters that can affect the engine's performance. Prediction involves using the trained model to predict the remaining useful lifetime of the engine based on the current sensor data. This can be done using a variety of techniques such as survival analysis, time-series analysis, or other methods that account for the degradation of the engine over time.
The prediction of RUL using machine learning algorithm can help improve the efficiency and safety of aircraft operation by enabling proactive maintenance and reducing the risk of unexpected failures.

To estimate remaining useful life of an turbofan engine.
To measure how many life cycles remains before engine failure.
To save time and energy by avoiding unnecessary activities.
To Predict if it can enable proactive maintenance by identifying potential issues before they become critical.

## LITERATURE WORK

In this section, we describe about the existing work. Our Paper deals with the problem associated with the existing system and also gives user a clear knowledge on how to deal with the existing problems and how to provide solution to the existing problems.

The author in the paper[1], This paper presents a comprehensive study on the application of intelligent tools for detecting and classifying broken rotor bars in three-phase induction motors that are fed by an inverter. The detection and classification of broken rotor bars are crucial for ensuring the reliable and efficient operation of induction motors. The proposed work focuses on leveraging advanced techniques such as artificial neural networks (ANNs), support vector machines (SVMs), and fuzzy logic systems to develop a robust and accurate system for fault detection and classification. [2]. This paper proposes a real-time predictive maintenance framework for wind turbines leveraging big data frameworks. Wind turbines are complex systems prone to various faults and failures that can lead to costly downtime and maintenance. The proposed work aims to enhance the maintenance strategies by employing big data analytics techniques to collect, process, and analyze large volumes of data generated by wind turbines. By utilizing real-time data monitoring, predictive analytics, and machine learning algorithms, the proposed framework enables early detection of potential failures and allows for proactive maintenance, leading to improved turbine performance and reduced operational costs. [3]. This paper proposes a comprehensive framework for developing predictive models to estimate the time to failure of critical systems. Predicting the remaining useful life of assets is crucial for effective maintenance planning, reducing downtime, and optimizing resource allocation. The proposed work focuses on leveraging machine learning and statistical techniques to develop accurate and reliable models that can estimate the time to failure of assets based on historical data. The developed models enable proactive maintenance strategies, enhancing operational efficiency and reducing maintenance costs.

[4]. This paper proposes a machine learning-based approach for event-based prognostics in gas circulator condition monitoring. Gas circulators play a critical role in various industrial applications, and accurate prognosis of their remaining useful life (RUL) is essential for optimal maintenance planning and preventing unexpected failures. The proposed work focuses on developing a machine learning model that can predict the occurrence of critical events and estimate the remaining life of gas circulators based on real-time sensor data. The model enables proactive maintenance strategies, improving operational efficiency and reducing downtime. The uniqueness of [4 Review existing research on prognostics and condition monitoring in gas circulators.

Discuss the utilization of machine learning algorithms, event detection techniques, and feature engineering approaches in prognostics. [5] This paper proposes a novel approach for failure prediction of railway turnouts using the AdaBoost algorithm and least square-based techniques. Railway turnouts, or switches, are critical components in railway infrastructure, and timely detection of potential failures is crucial for ensuring safe and reliable operations. The proposed work aims to develop a predictive model that can effectively identify the probability of failure in railway turnouts based on historical data. By combining the ensemble learning capability of AdaBoost and the robustness of least square regression, the proposed approach enhances the accuracy and reliability of failure prediction, enabling proactive maintenance strategies and minimizing disruptions in railway operations.

[6] This paper proposes a novel approach for predictive maintenance using machine learning, specifically employing a multiple classifier approach. Predictive maintenance plays a crucial role in optimizing asset performance, minimizing downtime, and reducing maintenance costs. The proposed work focuses on developing a robust and accurate predictive maintenance model by leveraging the ensemble learning capabilities of multiple classifiers. The combination of different classifiers enhances prediction accuracy, provides robustness against variability in data, and enables more reliable maintenance decision-making. [7] This paper proposes a novel approach for predicting the remaining useful life (RUL) of railcars by fusing data from multiple sources. Accurate prediction of the RUL is crucial for optimizing railcar maintenance, reducing downtime, and ensuring safe and efficient operations. The proposed work focuses on integrating diverse data sources, including sensor data, historical maintenance records, operational parameters, and external factors, to develop a comprehensive predictive model. By leveraging the fusion of multiple data sources, the proposed approach enhances prediction accuracy, robustness, and enables effective maintenance planning for railcar assets. [8] This paper proposes a novel approach for forecasting obsolescence risk and predicting the product life cycle using machine learning techniques. Obsolescence risk refers to the likelihood of a product becoming outdated or obsolete due to technological advancements, changing market dynamics, or other factors. Accurate forecasting of obsolescence risk and product life cycle is essential for effective inventory management, product development, and strategic decision-making. The proposed work aims to leverage machine learning algorithms to develop predictive models that can estimate obsolescence risk and forecast the product life cycle, enabling proactive measures to mitigate risks and maximize the value of products.[9] This paper presents a comprehensive comparison of various machine learning algorithms for proactive hard disk drive (HDD) failure detection. Early detection of HDD failures is critical for preventing data loss, minimizing downtime, and optimizing maintenance activities. The proposed work aims to evaluate the performance of different machine learning algorithms in accurately predicting HDD failures and identifying potential warning signs. By comparing the algorithms' predictive capabilities, this study aims to provide insights into the most effective approach for proactive HDD failure detection, aiding in the development of reliable and efficient maintenance strategies.

[10]This paper proposes an ensemble random forest algorithm for the analysis of insurance big data. The insurance industry generates massive amounts of data, including customer information, claims history, policy details, and risk factors. Extracting valuable insights from this data is crucial for decision-making, risk assessment, and developing effective insurance strategies. The proposed work aims to leverage the power of ensemble learning and the random forest algorithm to address the challenges posed by insurance big data. By combining multiple decision trees and aggregating their predictions, the ensemble random forest algorithm enhances predictive accuracy, robustness, and interpretability for insurance data analysis.

## 2. SYSTEM ARCHITECTURE

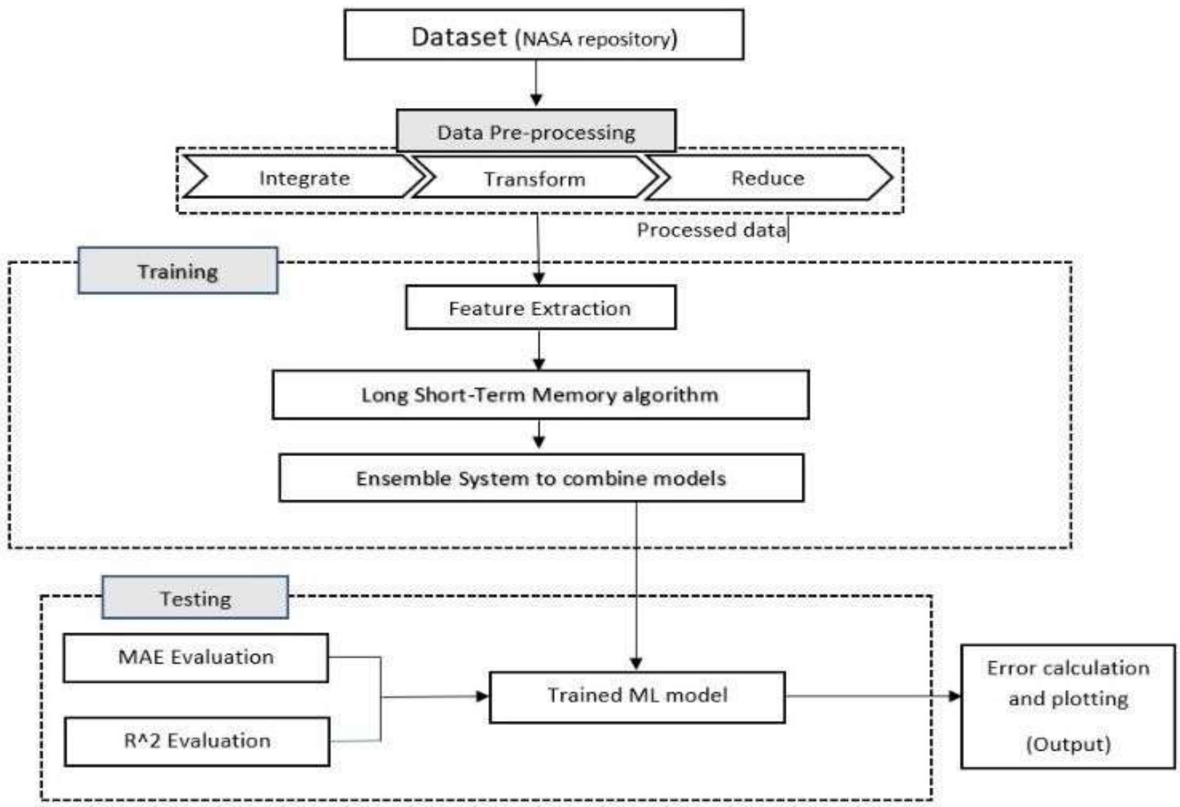


**Fig-1**: System Architecture

The system architecture defines the overall structure of the system, including its components, their interactions, and the data flow between them. In this system, we have identified the following components:

- **Data Preprocessing**: Preprocessing data is a common first step in the deep learning workflow to prepare raw data in a format that the network can accept. For example, you can resize image input to match the size of an image input layer. You can also preprocess data to enhance desired features or reduce artifacts that can bias the neural network.
- **Data Splitting:** This model is commonly used In deep learning to split data into a train and test set. The training data set is used to train and develop models. Training sets are commonly used to estimate different parameters or to compare different model performance. The testing data set is used after the training is done. The training and test data are compared to check that the final model works correctly.
- **Model Training** : In this models 80% are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without

the need for manual feature extraction.

- **Testing the Trained Model:** In this module we test the trained deep learning model using the 20% test dataset.

## 3. RESULTS AND PERFORMANCE ANALYSIS

While predicting RUL, the main objective is to reduce the error between the actual RUL and the predicted RUL. For each dataset, the test results were compared with the actual values of the RUL available in the data set. The mean absolute error were plotted and it is observed that the best results were obtained by long – short term memory.

When predicting the remaining lifetime of a turbofan engine using a machine learning algorithm, the performance analysis typically involves evaluating the accuracy, precision, recall, and other relevant metrics of the predictive model. The specific metrics used can vary depending on the approach and problem formulation.

Evaluate the trained model on the testing dataset to assess its performance. Calculate the relevant regression metrics mentioned above to gauge the accuracy and precision of the predictions. Additionally, you can plot the predicted remaining lifetime against the actual remaining lifetime to visually inspect the model's performance.

According to Figure 2, It indicates the proportion of the variance in the target variable. To create an R-squared graph, you would typically plot the predicted remaining lifetime values against the actual remaining lifetime values for the test dataset. The x-axis would represent the actual remaining lifetime values, while the y-axis would represent the predicted remaining lifetime values. Each data point on the graph would correspond to an individual instance from the test dataset.

According to Figure 3, It measures the average absolute difference between the predicted and actual values of the target variable (remaining lifetime). The lower the MAE, the better the model's predictions align with the actual values.

According to Figure 4, A model loss graph for predicting the remaining useful lifetime of a turbofan engine using a machine learning algorithm typically shows the training and validation loss values over different epochs or iterations during the training process. Loss refers to the error or discrepancy between the predicted remaining lifetime and the actual remaining lifetime.

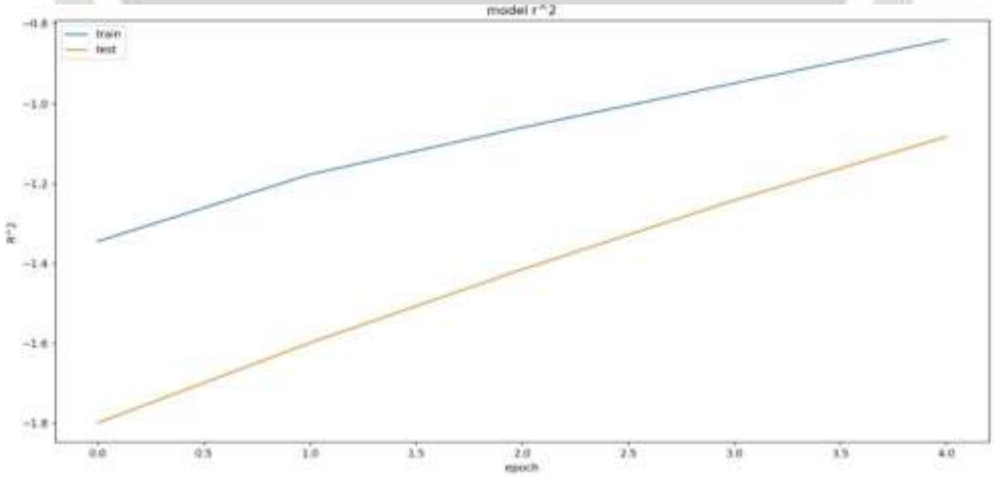


**Fig-2**: R- squared analysis

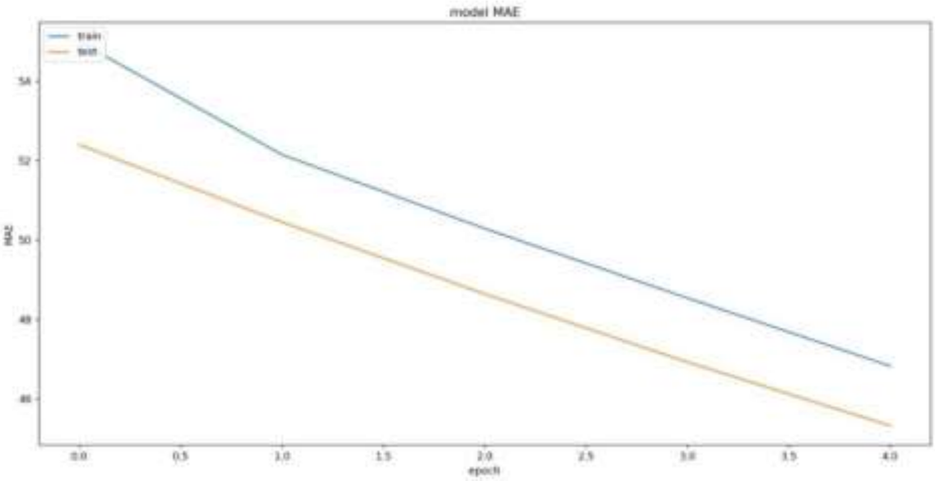


**Fig -3**: Mean Absolute Error

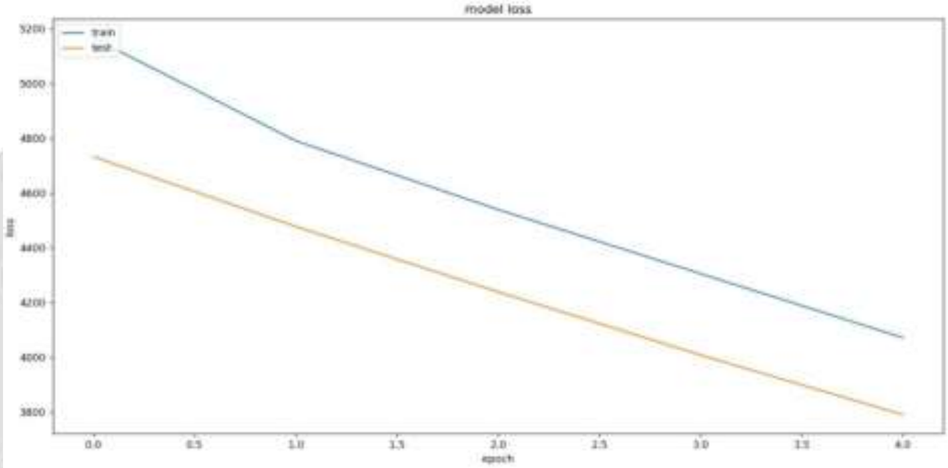


**Fig -4**: Model loss Analysis

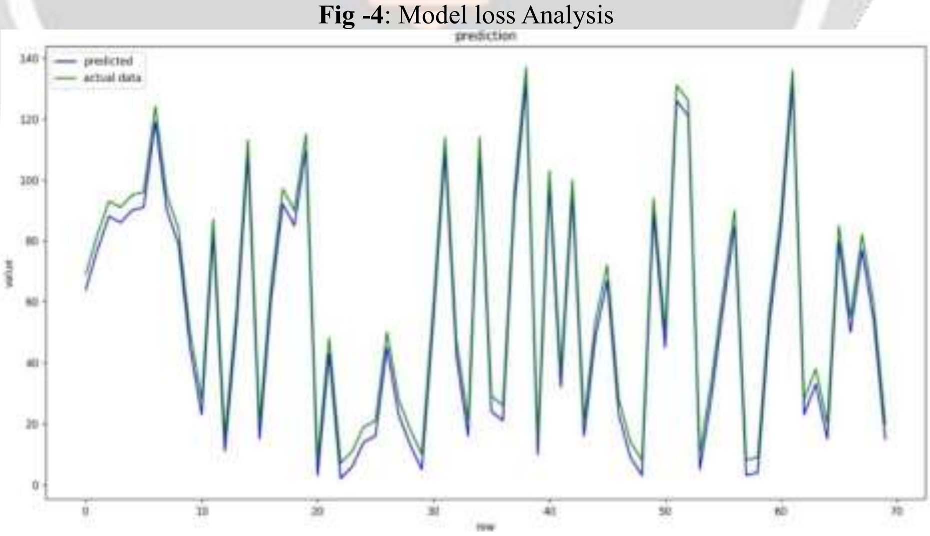


**Fig -5**: Predicted Graph

## 4. CONCLUSION AND FUTURE ENHANCEMENTS

5.

The Remaining Useful Lifetime prediction has been carried out so as to plan the maintenance requirements of the turbo fan engine. By doing predictive maintenance, failures can be predicted and maintenance can be scheduled in advance. This reduces the cost and effort for doing maintenance. By predicting the RUL, ML algorithms can assist in scheduling maintenance activities proactively. This can minimize downtime and reduce the overall maintenance costs associated with engine replacements or repairs. It can analyze various sensor data and operational parameters to optimize the performance of turbofan engines. This estimation helps in planning maintenance activities and avoiding unexpected failures.

In future, the algorithm can be tested for more real time data and always be one step ahead in predicting the maintenance requriments.

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