# Remaining Useful Life Prediction of Aircraft Engine

Group no. 19

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# Contents

# Introduction

- What is RUL in Aircrafts?
  estimated operational lifespan of aircraft components
- Why RUL prediction in Aircrafts matters?
  Safety Assurance
  Predictive Maintenance
  Optimized Maintenance Scheduling
  Extended Engine Life
  Cost Reduction
  Data Driven Decision Making

# Problem Statement

To provide an accurate machine learning model or predictive maintenance system for aviation engines with the goal of precisely forecasting the Remaining Useful Life (RUL) in order to improve efficiency and operational reliability.

# Objectives

- Develop a novel DBRNN+ProgNet+DCNN ensemble prognostic model for remaining useful life estimation.
- Obtain less than 19 RMSE scores from existing Methodology.
- Develop a robust system that can provide accurate predictions under all operating conditions. The existing method only works best for two operating conditions.
- Reduce Training time of dataset to less than 1hr.

# System Architecture

https://github.com/SnehaBhaskar26/BE-Project-Resources/blob/f84b134d63afdc5d85e308e930a367fdf5cff47d/System%20Arc
System Architecture

# Mathematical Modelling

The system equation $S$ can be represented as follows:

$$S = \begin{cases} h_t^{\text{Bi-TRNN}} & \text{Bi-TRNN is used,} \\ h_t^{\text{Bi-LSTM}} & \text{Bi-LSTM is used,} \\ h_t^{\text{Bi-GRU}} & \text{Bi-GRU is used,} \\ h_t^{\text{DCNN}} & \text{DCNN is used,} \\ h_t^{\text{ProgNet}} & \text{ProgNet is used,} \\ \hat{y} & \text{output layer is reached,} \end{cases}$$

Where:

- $h_t^{\text{Bi-GRU}}$, $h_t^{\text{Bi-LSTM}}$, $h_t^{\text{Bi-TRNN}}$, $h_t^{\text{DCNN}}$, and $h_t^{\text{ProgNet}}$ represent the hidden states or outputs at time $t$ for each respective model.
- $\hat{y}$ is the final output of the model.
- Each model's specific architecture and equations are encapsulated within their respective components.

# Mathematical Modeling

**Labeling Dataset:**

$$y_i = \text{Labeling}(x_i)$$

**Correlation Analysis:**

$$r = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}}$$

**Data Normalization:**

$$Z = \frac{X - \mu}{\sigma}$$

# Mathematical Modeling: Bi-TRNN

**Bi-TRNN:**

$$h_t^{\text{(Forward)}} = A(X_t \cdot W_{XH}^{\text{(Forward)}} + h_{t-1}^{\text{(Forward)}} \cdot W_{HH}^{\text{(Forward)}} + b_H^{\text{(Forward)}})$$
$$h_t^{\text{(Backward)}} = A(X_t \cdot W_{XH}^{\text{(Backward)}} + h_{t+1}^{\text{(Backward)}} \cdot W_{HH}^{\text{(Backward)}} + b_H^{\text{(Backward)}})$$

$$h_t^{\text{Bi-TRNN}} = Y_t = h_t \cdot W_{AY} + b_y$$

# Mathematical Modeling: Bi-LSTM

**Bi-LSTM:**

**Forget Gate:**

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

**Input Gate:**

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

**Cell State Update:**

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

**Output Gate:**

$$h_t^{\text{Bi-LSTM}} = o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

**Bi-GRU:**

Forward GRU:

$$
\begin{aligned}
z_t^f &= \sigma(W_z^f x_t + U_z^f h_{t-1}^f + b_z^f) \\
r_t^f &= \sigma(W_r^f x_t + U_r^f h_{t-1}^f + b_r^f) \\
\tilde{h}_t^f &= \tanh(W^f x_t + r_t^f \circ U^f h_{t-1}^f + b^f) \\
h_t^f &= (1 - z_t^f) \circ h_{t-1}^f + z_t^f \circ \tilde{h}_t^f
\end{aligned}
$$

Backward GRU:

$$
\begin{aligned}
z_t^b &= \sigma(W_z^b x_t + U_z^b h_{t+1}^b + b_z^b) \\
r_t^b &= \sigma(W_r^b x_t + U_r^b h_{t+1}^b + b_r^b) \\
\tilde{h}_t^b &= \tanh(W^b x_t + r_t^b \circ U^b h_{t+1}^b + b^b) \\
h_t^b &= (1 - z_t^b) \circ h_{t+1}^b + z_t^b \circ \tilde{h}_t^b
\end{aligned}
$$

# Mathematical Modelling: Bi-GRU

Output concatenation:

$$h_t^{\text{Bi-GRU}} = [h_t^f, h_t^b]$$

**DCNN:**

$$\textbf{Convolution:}\ \ z_k = \sum_{j=1}^{M} x_j \cdot w_{jk} + b_k$$

$$\textbf{Activation:}\ \ a_k = f(z_k)$$

$$\textbf{Pooling:}\ \ p_k = \max(a_k)$$

$$\textbf{Output:}\ \ h_t^{\text{DCNN}} = y = \text{softmax}(p)$$

**ProgNet:**
**First LSTM Layer:**

$$h_t = \mathrm{LSTM}(x_t, h_{t-1})$$

**Second LSTM Layer:**

$$h_t = \mathrm{LSTM}(h_{t-1})$$

**Output Layer:**

$$h_t^{\mathrm{ProgNet}} = \hat{y} = Wh_T + b$$

# Mathematical Modelling

The ensemble model using a **Random Forest Regressor (RFR)** can be represented as follows:

$$S = \frac{1}{K} \sum_{i=1}^{K} f_k(X)$$

**Performance Evaluation:**

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i|$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

# Algorithm Development

**Steps to biuld Base Learner Models:**

- Define a function to build a base learner model
- Preprocess data for model
- Build the model
- Define early stopping to prevent overfitting
- Train the model
- Evaluate on train data
- Evaluate on test data
- Display the results DataFrame

# Algorithm Development

**Ensemble model using Random Forest Regressor:**

- Concatenate predictions from all base learners for training data
- Concatenate predictions from all base learners for test data
- Define the Random Forest model
- Train the Random Forest model
- Predictions on training data
- Predictions on test data
- Add results to the DataFrame
- Display the results DataFrame

# Algorithm Development

| **Hyperparameter** | **Value** |
|---|---|
| Number of Estimators | 100 |
| Maximum Depth | 10 |
| Random State | 42 |

Table: Hyperparameters for Random Forest Model

# Code Implementation

https://github.com/SnehaBhaskar26/BE-Project

# Results and Performance Evaluation

| **Datasets** | FD001 | FD002 | FD003 | FD004 |
|---|---|---|---|---|
| **Metric (RMSE)** | | | | |
| **Proposed Method** | 14.49 | 14.11 | 15.73 | 15.69 |
| **Base Paper** | 17.97 | 19.81 | 19.18 | 20.4 |

Table: Comparison of RMSE between Proposed Methods and Base Paper

# Conclusion

- Achieved RMSE scores lower than 19, surpassing the baseline paper's performance across all subsets.
- Marginally reduced training time, enhancing efficiency without compromising on predictive accuracy using feature extraction,early stopping.
- The proposed ensemble model, combining DBRNN, ProgNet, and DCNN, exhibited high predictive accuracy and robustness.
- Developed a robust system that can provide accurate predictions under all operating conditions

# Review Paper

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

## A Comprehensive Survey of Predictive Maintenance Techniques for Aircraft Engines Utilizing the C-MAPSS Dataset

**Muskan Pathan[1], Sneha Bhaskar[2], Vijayraje Jadhav[3], Vedant Kulkarni[4], Komal Gaikwad[5]**

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**Abstract** - The application of deep learning and sophisticated machine learning techniques is driving the rapid advancement of aircraft engine prognostics and predictive maintenance. Remain ing Useful Life (RUL) of aviation engines has been the subject of numerous studies aimed at improving prediction accuracy and efficacy to improve aviation safety and maintenance plans. Innovative approaches and technologies are demonstrated by these projects, which use a variety of methodologies and datasets, including C-MAPSS and N-CMAPSS. Combining feature engi neering, ensemble learning, and deep learning models such as measuring uncertainty. Additionally, in order to pinpoint important features and improve model transparency, the study investigates the use of explainable AI techniques such aggregated feature importances with cross-validation (AFICv) and Shapley additive explanation (SHAP). In order to capture prediction uncertainties, the inte gration of Gaussian Processes (GPs) and Bayesian Deep Neural Networks (DNNs) is also investigated. This provides insights into uncertainty-aware prognosis and predictive analytics for industrial assets. The development and publication of datasets such as the N-CMAPSS dataset also makes it possible to conduct more

Figure: Review Paper

# Review Paper

ISSN: 2582-3930

ACCEPTANCE CERTIFICATE

Impact Factor: 8.448
DOI Prefix: 10.55041

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*VOLUME 08 ISSUE 05 MAY - 2024*

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Figure: Acceptance Certificate of Review Paper

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Thank you