Project Stage II Report on

Remaining Useful Life Prediction of Aircraft Engine

Submitted in partial fulfillment of the requirements for the Degree of

Bachelor of Engineering in

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

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VPKBIET, Baramati

Certificate

This is to certify that the Project Stage II Report on

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in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering in Artificial Intelligence and Data Science at Vidya Pratishthan's Kamalnayan Bajaj Institute of Engineering and Technology, Baramati, under the Savitribai Phule Pune University, Pune. This work is done during year 2023-24 Semester-II, under our guidance.

Mrs. K.S. Gaikwad	Dr. P. M. Paithane	Dr. R. S. Bichkar
Project Guide	Head of Dept.	Principal

Examiner 1: - - - - - - -

Examiner 2: - - - - - - -

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Abstract

Remaining usable life (RUL) of aviation engines (AEs) must be accurately predicted in order to optimize main- tenance schedules, lower total maintenance costs, and improve operating safety. Inaccurate RUL predictions result from tra- ditional approaches' frequent inability to capture the intricate nonlinear correlations found in engine sensor data. In this work, we suggest a unique method that uses a random forest regressor in conjunction with an ensemble of deep learning models to overcome these difficulties. Different deep learning architectures such as Bidirectional Long Short-Term Memory (BiLSTM), Bidirectional Gated Recurrent Unit (BiGRU), Bidi- rectional Traditional Recurrent Neural Network (Bi-TRNN), Progressive Neural Network (ProgNet), and Deep Convolutional Neural Network (DCNN) are integrated in our method. We are able to overcome the constraints of single-model techniques by extracting complete and subtle information from the sensory input using this broad ensemble of models. Our ensemble technique shows robustness across various operating conditions and failure modes by encapsulating predictions from many deep learning models into a projected RUL domain by using the random forest regressor to synthesize them. We demonstrate our methodology's capacity to beat existing approaches in terms of Root Mean Square Error (RMSE) for RUL prediction by validating it using NASA's C-MAPSS datasets. The outcomes of our experiments demonstrate the effectiveness of our method, suggesting that it has the potential to greatly enhance aviation engine maintenance procedures. Prognostics and health manage- ment (PHM) approaches are advanced by this research, which offers a solid foundation for efficient maintenance scheduling and financial savings.

Keywords: Remaining Useful Life (RUL), Bidirectional Long Short-Term Memory (Bi-LSTM), Bidirectional Gated Recurrent Unit (Bi-GRU), Bidirectional Traditional Recurrent Neural Network (Bi-TRNN), Progressive Neural Network (ProgNet), Deep Convolutional Neural Network (DCNN), Mean Square Error (RMSE), R squared

List of Figures

Notations and Abbreviations

- AE - Aircraft Engine
- BDRNNs - Bidirectional Recurrent Neural Networks
- EL - Ensemble Learning
- PHM - Prognostics and Health Management
- RUL - Remaining Useful Life
- DCNN - Deep convolutional neural networks
- TRNN - Temporal Recurrent Neural Network
- GRU - Gated Recurrent Unit
- LSTM - Long Short-Term Memory

Contents

Chapter 1

Introduction

1.1 Introduction

Problem Statement: 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.

In order to guarantee the safety, effectiveness, and economy of aviation operations, the Remaining Useful Life (RUL) of aircraft components must be accurately estimated. The term "ratio length of life" (RUL) in aviation refers to the expected operational lifetime of different critical flying components, such as avionics and engines. This research report explores the importance of RUL prediction in aircraft, highlighting how important it is to improving safety assurance, making maintenance procedures more efficient, and eventually extending engine life. Because reliable RUL forecasts allow for the proactive replacement of important com- ponents before they reach the end of their operational life, safety assurance is a crucial component. RUL insights-driven predictive maintenance also makes it possible to in- tervene promptly, which lowers the possibility of unplanned breakdowns and improves operational reliability all around. Because RUL projections enable more efficient mainte- nance scheduling, significant cost savings are achieved by avoiding needless replacements and repairs in addition to minimizing downtime. Furthermore, a paradigm change toward data-driven decision-making is fostered by the use of RUL prediction in aircraft operations. Aviation stakeholders can increase overall system performance and allocate resources more effectively by using data analytics and predictive modeling to make well-informed decisions.

1.2 Motivation

- Limited Access to Quality Data: The initiative is driven by the difficulty of limited availability to high-quality data, which makes it more difficult to accurately anticipate the remaining useful life (RUL) of airplane components. Decision-making and maintenance planning in aircraft operations are hindered by incomplete or untrustworthy datasets.
- Noisy Sensor Data and Anomalies: Advanced data cleaning and preprocessing procedures are necessary due to the complexity created by anomalies and noisy sensor data. To guarantee the resilience and dependability of RUL prediction models, these anomalies must be fixed.
- Complex, Nonlinear Degradation Patterns: Aircraft components can be challenging to simulate because of their complex, nonlinear deterioration patterns. The research intends to create cutting-edge methods and sophisticated algorithms to precisely record and depict these intricate deterioration patterns.
- High-Dimensional Data: Feature selection is made more difficult by the data's high-dimensionality. In order to find the most pertinent variables and improve model interpretability, the project will investigate and apply sophisticated feature selection techniques. This will expedite the modeling process.
- Scarcity of Failure Data: Model training in aviation settings is hampered by the scarcity of failure data. In order to improve the robustness and generalizability of RUL prediction models, the project will investigate techniques including transfer learning and data augmentation.

Chapter 2

Literature Survey

The review of literature on the prediction of Remaining Useful Life (RUL) in aviation engines includes a detailed investigation of the various approaches used in the most recent research. The application of DBRNN, LSTM, and GRU algorithms demonstrated effective sequence data and time-dependent pattern handling [1], however their applicability was limited to two operating circumstances. Using LSTM, hyperparameter tweaking, and efficient preparation procedures[2] achieved an RMSE of 18, which is a noteworthy level of generalization capability. The study did, however, draw attention to the difficulties in intricate implementation and fine-tuning. Neural networks, Gaussian processes (GPs), DSPP, and MCD[3], who demonstrated versatility in modeling complicated data but acknowledged limits in handling temporal dependencies[4] effectively retrieved features from raw sensor signals and recorded temporal dependencies; nevertheless, assumptions about previous samples falling within the same operating state caused some worry. By combining temporal and time-frequency data [5] used CLSTM to achieve better results but at the expense of more training time. CNN, LSTM, and xAI [6], with a focus on improved reliability and overfitting prevention. However, specifics on xAI techniques were lacking [4] successfully recovered features from raw sensor signals and recorded temporal dependencies with a focus on Bi-LSTM; neverthe- less, assumptions about prior samples falling inside same operating state raised some concerns[5] employed CLSTM to maximize performance at cost of increased training time by mixing temporal and time-frequency data[6] investigated CNN, LSTM, and xAI techniques.

Chapter 3

Proposed System

3.1 Problem Definition

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.

3.2 Project Objectives

- To accurately estimate the remaining useful life, combine DBRNN with the ProgNet/D-CNN ensemble to create a novel prognostic model.
- Achieve an RSME score of less than 19, outperforming the effectiveness of current approaches for estimating remaining useful life.
- Build a reliable system that can provide precise forecasts in a variety of operating environments, surpassing the constraints of existing techniques that are geared toward just two scenarios.
- Cut the dataset's training time in half, to less than 15 hours, to improve the prognostic model's effectiveness and usefulness.

3.3 Scope of Project

- Explainable AI- Explainable AI: Building trust and comprehension of RUL predictions requires the development of explainable AI methods to decipher the deep learning models' decision-making process.
- Fleet-wide RUL Prediction: Extend RUL prediction capabilities to entire aircraft fleets, enabling predictive maintenance across multiple aircraft and engine types.
- Self-healing Aircraft Systems: Integrate RUL prediction into self-healing aircraft systems that can automatically adapt to component degradation and maintain optimal performance.
- Multimodal Data Integration: Incorporate multimodal data, such as vibration, acoustic, and oil analysis data, to provide a more comprehensive picture of engine health and improve RUL prediction accuracy

3.4 Project Constraints

- Data Availability: The accuracy of RUL prediction is heavily dependent on the quality and quantity of available data. Limited or noisy data can significantly impact the performance of the deep learning models.
- Model Generalization: Deep learning models trained on specific datasets may not generalize well to unseen data from different aircraft engines or operating conditions. Addressing this issue requires careful data selection and model validation strategies
- Human-AI Collaboration: Effective RUL prediction systems should integrate seamlessly with human expertise and decision-making processes in aircraft maintenance. Balancing the automation of RUL prediction with human oversight is essential for maintaining safety and control

Chapter 4

Proposed System Architecture

4.1 Architecture

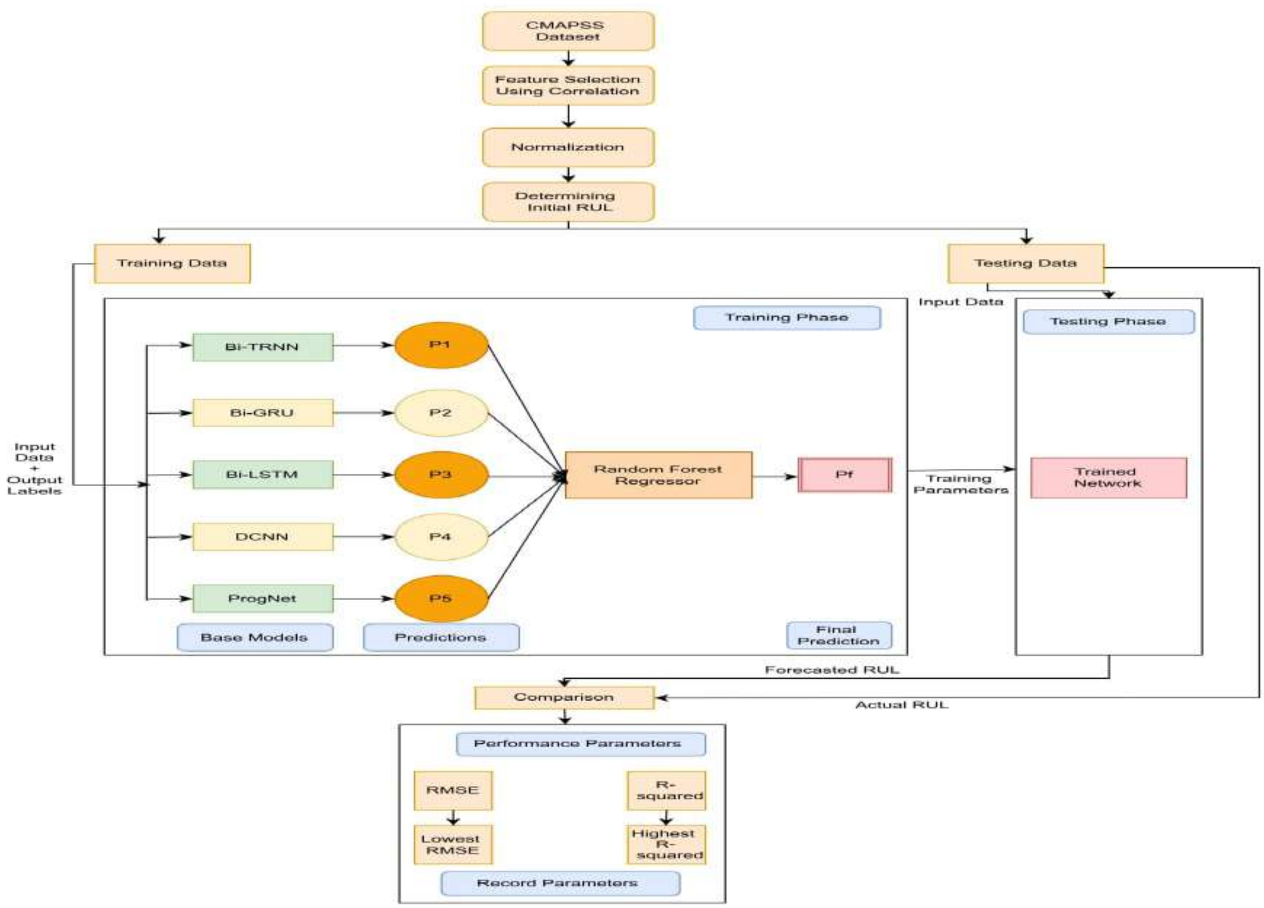

Fig. 4.1 System Architecture

Flow of Architecture is as Follows:

1. Dataset Description
2. Data Analysis and Pre-processing
3. Feature Selection
4. Normalization
5. Remaining Useful Life Calculation
6. Base Models Building
7. Ensemble Learning
8. Performance Evaluation

4.2 Mathematical Model

- **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:**

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

- **Bi-TRNN:**

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

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

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

- **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:

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

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

$$y_t = \sigma(\overrightarrow{h}_t M \overleftarrow{h}_t)$$

- **Bi-GRU :**

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

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

Output concatenation:

$$h_t^{\text{Bi-GRU}} = \quad h_t = [h_t^f, h_t^b] \quad \text{(Concatenated output of forward and backward GRUs)}$$

- **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:

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

  Second LSTM Layer:

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

  Output Layer:

$$h_t^{\text{ProgNet}} = \hat{y} = W h_T + b$$

- The ensemble model using a **Regression Decision Tree (RDT)** can be represented as follows:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} h_i(X)$$

4.3 Proposed Algorithms:

1. Bi-TRNN: By utilizing information from both past and future states sequentially, a bidirectional traditional recurrent neural network (Bi-RNN) processes data in both forward and backward directions simultaneously. It is made up of two distinct hidden layers, each of which only processes input in one direction. Outputs from both directions are combined for better understanding of context and capturing complex patterns. This architecture is effective as it better captures temporal dependencies in sequential data, enhancing overall performance.

2. Bi-GRU: By processing sequential data in both directions and capturing dependencies from both past and future states, the Bidirectional Gated Recurrent Unit (Bi-GRU) expands upon the conventional GRU architecture. In order to manage information flow and address the vanishing gradient issue in RNNs, GRU makes use of update and reset gates. Bi-GRU combines these advantages with bidirectional processing, enabling it to understand context from both directions and learn complex patterns in sequential data effectively.

3. Bi-LSTM: In order to process input sequences in both forward and backward directions and enhance context understanding, a Bidirectional Long Short-Term Memory (Bi-LSTM) model extends the conventional LSTM architecture. In a Bi-LSTM model, the input, forget, and output gates in each LSTM layer regulate the storage, discarding, and output of information, respectively. These gates help with long-range dependency management and solve the traditional RNN's vanishing gradient issue.

4. DCNN: Deep Convolutional Neural Networks (DCNNs) excel in time series data analysis by automatically extracting hierarchical features and learning spatial-temporal relationships. Through convolutions and pooling, they capture both short-term and long-term patterns. DCNNs identify local patterns at various time scales, enabling them to handle complex temporal dynamics like seasonality and trends. They can process variable-length time series data using techniques such as padding or truncation.

5. ProgNet: ProgNet, an acronym for Progressive Neural Network, is a model specifically engineered to efficiently manage sequential data. It uses layers of Long Short-Term Memory (LSTM) to identify dependencies and temporal patterns in the input sequences. ProgNet can extract progressively complex features from the data by using multiple LSTM layers. ProgNet can comprehend and forecast sequential data by utilizing LSTM architecture, which makes it appropriate for applications like natural language processing and time series forecasting.

6. Random Forest Regressor: As a member of the ensemble learning family, the Random Forest Regressor builds several decision trees during training and averages them for regression tasks. It efficiently decorrelates trees, lowering overfitting, by training each tree on a random subset of data and taking into account a random subset of features at each node. The Random Forest Regressor is a well-known tool for handling high-dimensional data with intricate interactions because of its robustness and scalability. It captures complex relationships between input features and the target variable, utilizing engine sensor readings, flight data, and maintenance records for precise RUL estimation. It is especially helpful in estimating the Remaining Useful Life (RUL) of aircraft engines. Its ensemble nature mitigates model bias and variance, ensuring reliable predictions essential for proactive maintenance planning in aviation.

Chapter 5

Project Requirement Specification

5.1 Hardware Requirements

- Processor: Any Processor above 500 MHz.
- RAM: 4 GB (Minimum)
- Hard Disk: 250 GB
- Graphics Card: 4GB
- Input device: Standard Keyboard and Mouse
- Output device: High Resolution Monitor

5.2 Software Requirements

- Operating System: Windows 10 or higher, Ubuntu 22.0+
- Python 3.8 +
- Anaconda Navigator
- IDE: VSCode, Pycharm, Jupyter Lab

5.3 Performance Requirements

- Accuracy: The RUL prediction system should achieve high accuracy in its predictions, minimizing the error between predicted RUL and actual remaining lifespan.This is crucial for making informed maintenance decisions and ensuring aircraft safety.
- Generalizability: The RUL prediction models should generalize well to unseen data from different aircraft engines and operating conditions. This is essential for the system to be effective in real-world applications across a diverse fleet of aircraft
- Latency: The RUL prediction system should provide timely predictions with minimal latency. Real-time or near-real-time predictions are necessary for proactive maintenance scheduling and informed decision-making during aircraft operations.
- Computational Efficiency: The RUL prediction system should be computationally efficient, considering the volume of sensor data and the complexity of deep learning models. This is important for deploying the system on real-world aircraft systems without compromising performance or resource utilization.

5.4 Security Requirements

- Protect sensitive data with robust access control, encryption, and integrity checks
- Safeguard deep learning models from adversarial attacks, manipulation, and unauthorized changes.
- Ensure system resilience with strong network security, system hardening, and incident response plans.
- Foster human-AI security through human oversight, explainable AI, and error prevention strategies.

Chapter 6

Project Planning

6.1 Team Structure

Sr No.	Team Member	Role
1	Vedant Kulkarni	Research, Documentation, Data Collection, Data Preprocessing
2	Sneha Bhaskar	Research, Data Preprocessing, Model Building
3	Muskan Pathan	Research, Documentation, Data Analysis
4	Vijayraje Jadhav	Model Validation, Deployment

Table 6.2 Team Structure

Chapter 7

Project Schedule

7.1 Timeline Chart

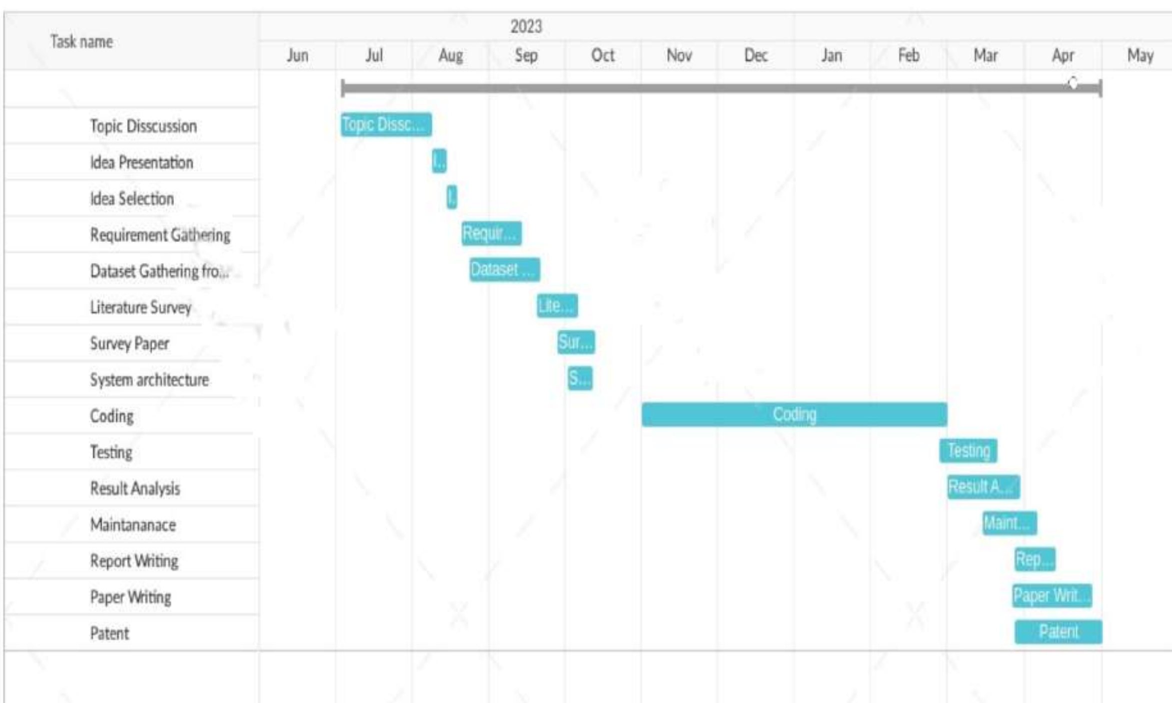

Fig. 7.1 Gantt Chart

Chapter 8

Project Design

8.1 Data Flow Diagrams

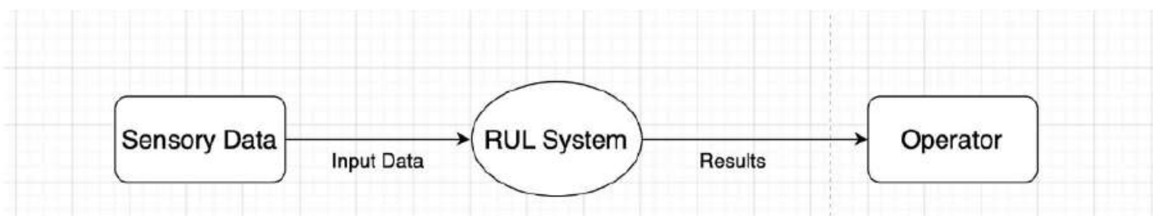

Fig. 8.1.1 Data Flow Diagram (Level 0)

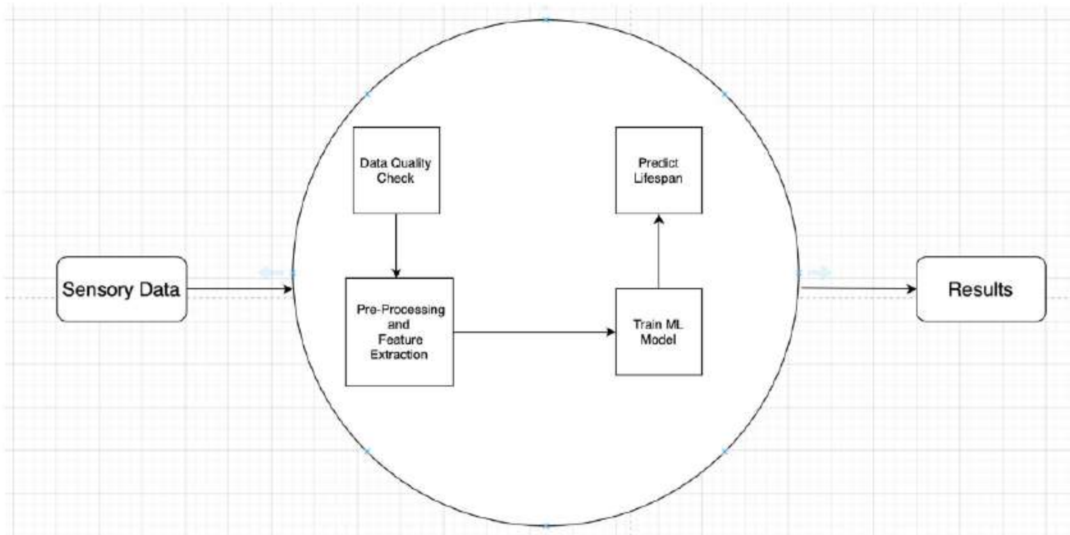

Fig. 8.1.2 Data Flow Diagram (Level 1)

8.2 Use Case Diagram

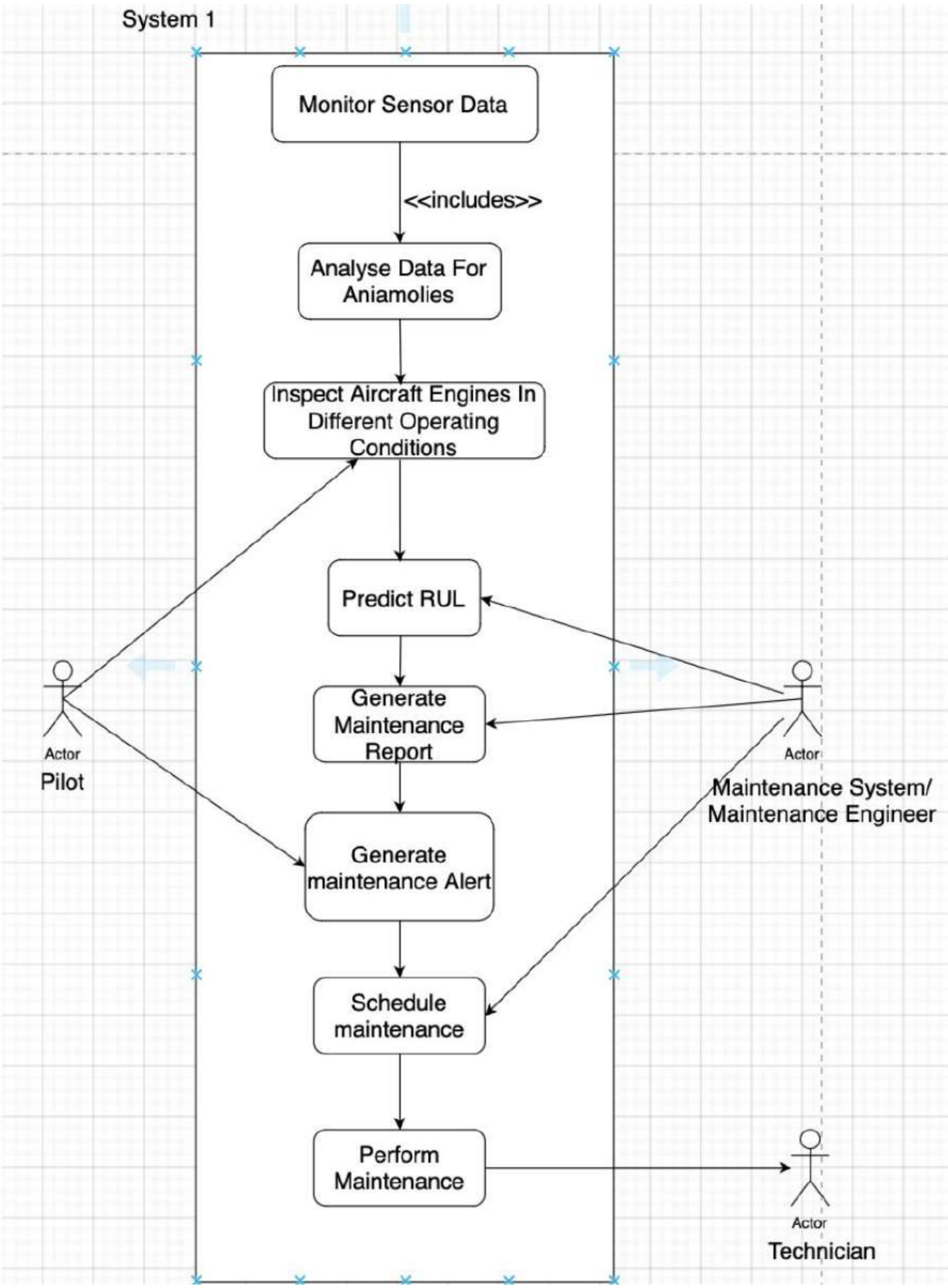

Fig. 8.2 Use case Diagram

8.3 Class Diagram

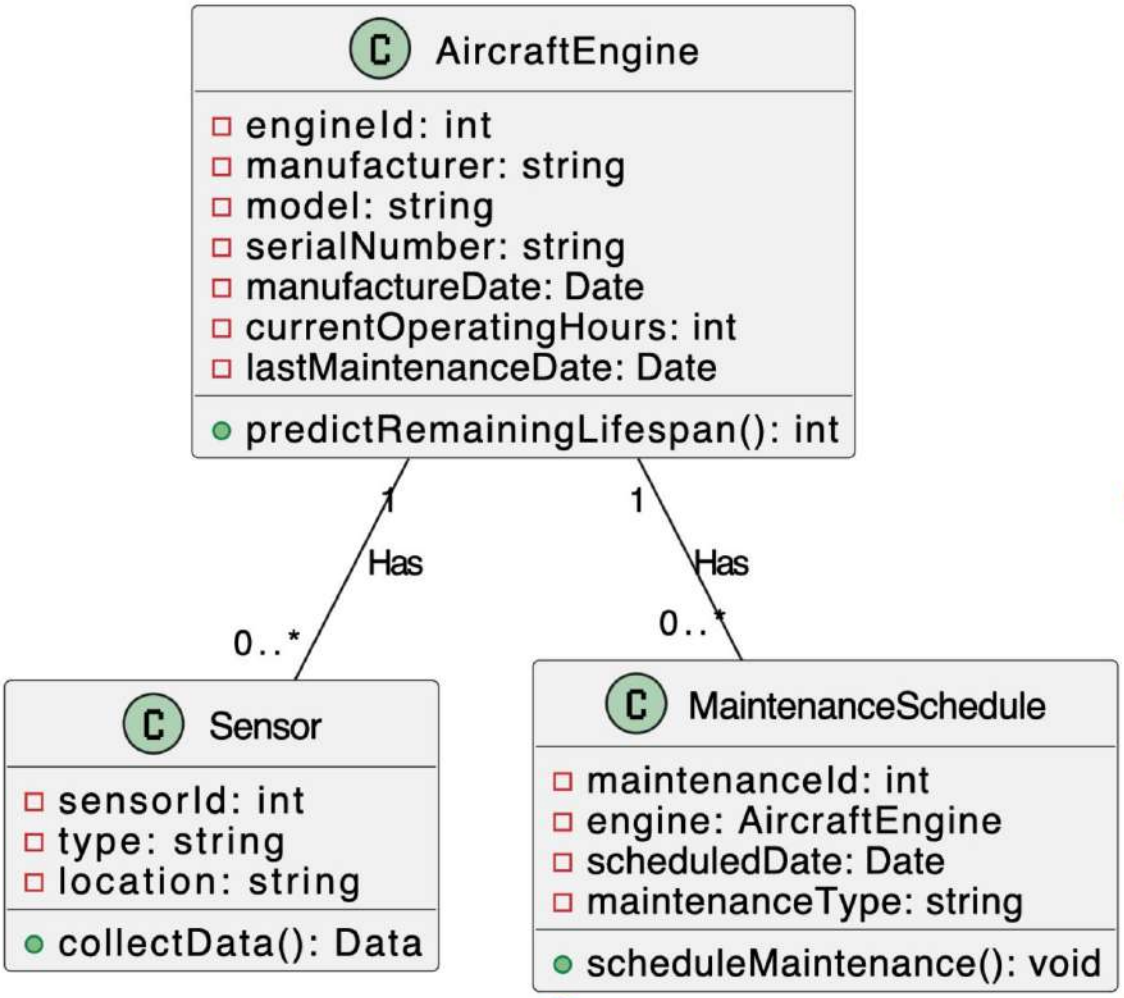

Fig. 8.3 Class Diagram

8.4 Activity diagram

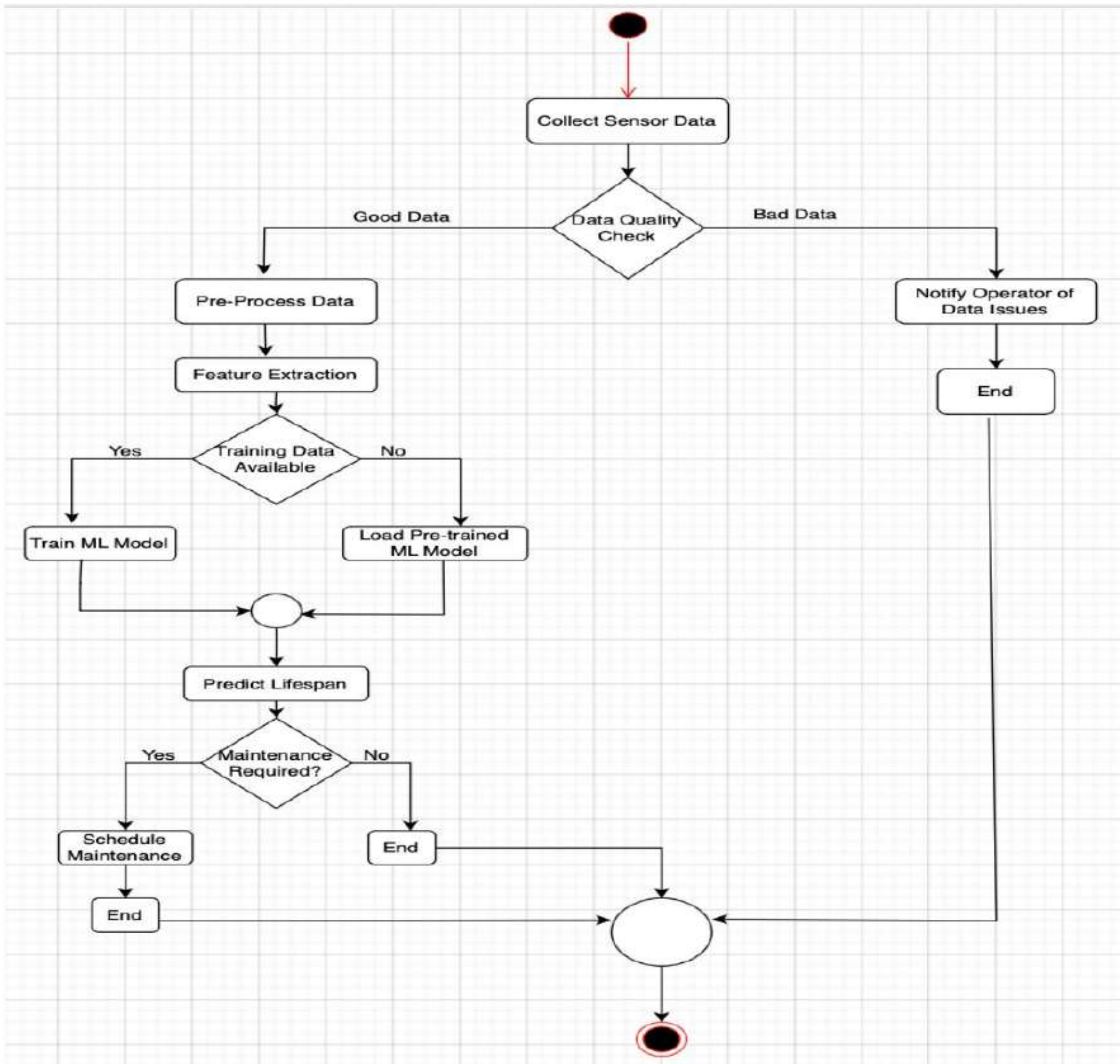

Fig. 8.4 Activity diagram

8.5 Sequence Diagram

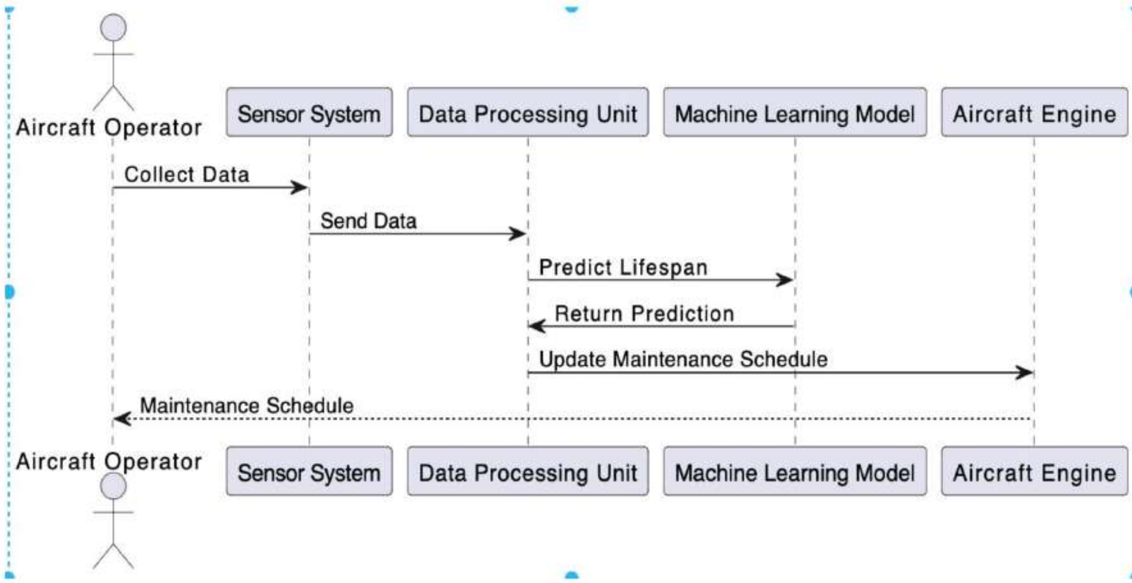

Fig. 8.5 Sequence Diagram

8.6 Component Diagram

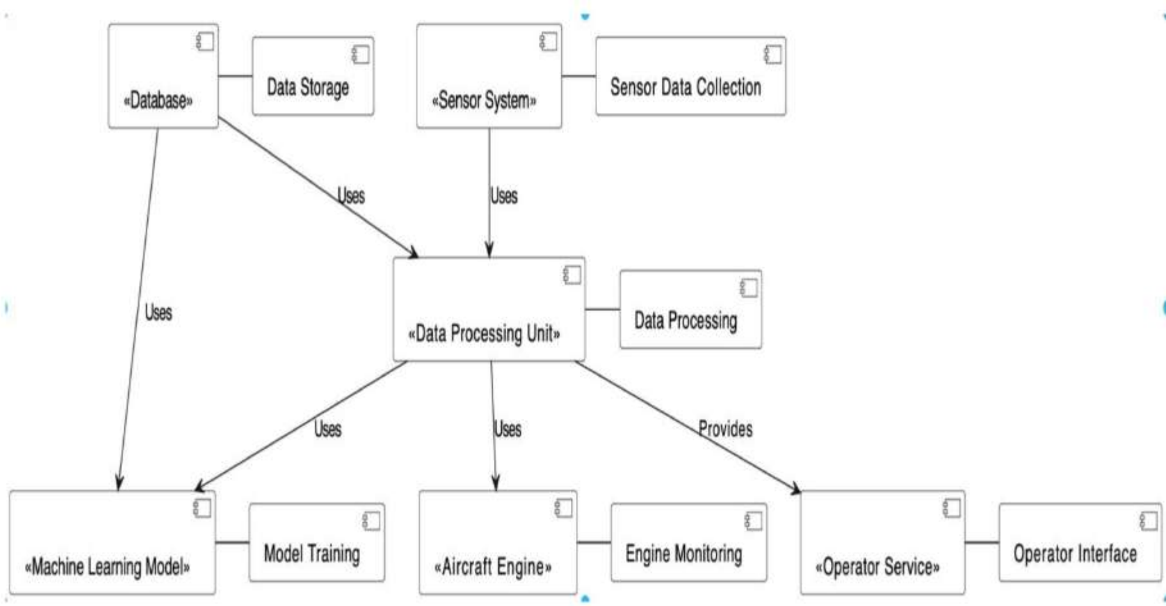

Fig. 8.6 Component Diagram

Chapter 9

Results and Experimentation

9.1 Experimental Setup

- **Dataset Description:** Begin by describing the dataset used for RUL prediction. This includes information such as the source of the data, the variables included (e.g., sensor readings, operational conditions), the time-series nature of the data (if applicable), and any preprocessing steps already performed (e.g., handling missing values, data cleaning).
- **Data Analysis and Pre-processing:** Conduct exploratory data analysis (EDA) to gain insights into the dataset. This may involve visualizing sensor data over time, identifying trends or patterns, and detecting outliers. Preprocessing steps such as data scaling, handling categorical variables, and dealing with imbalanced data can also be discussed.
- **Feature Selection:** Discuss the process of selecting relevant features for RUL prediction. This may involve techniques like correlation analysis, feature importance ranking from machine learning models, or domain knowledge-based feature selection. Emphasize the importance of selecting features that capture the degradation patterns of aircraft engines.
- **Normalization:** Explain the importance of data normalization in machine learning models, especially for features with different scales. Techniques such as Min-Max

scaling or Standardization can be mentioned, along with their impact on model performance and convergence.

- **Remaining Useful Life Calculation:** Describe how RUL is calculated or estimated based on the dataset and domain knowledge. This could involve methods like regression analysis, survival analysis, or specialized models for RUL prediction. Discuss any assumptions or constraints related to RUL calculation.
- **Base Models Building:** Detail the process of building base machine learning or deep learning models for RUL prediction. This includes Bi-LSTM, DCNN, Bi-TRNN, Bi-GRU, and Prognet
- **Ensemble Learning:** Explain the concept of ensemble learning and its application in improving RUL prediction accuracy. Used Random Forest Regressor to increase the result and more accurately predict the RUL
- **Performance Evaluation:** Describe the metrics used to evaluate the performance of RUL prediction models. Common metrics include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared (R2) score, and accuracy for classification-based RUL prediction. Discuss the significance of cross-validation, model validation on test data, and comparison of different models' performance.

9.2 Test Specifications

- Assess model performance, identify potential issues, and ensure reliability.
- Utilized synthetic image datasets with diverse characteristics for testing.
- Evaluated RSME and R- Squared through various scenarios.
- Defined threshold values for passing/failing each test case.
- Utilized standard hardware and software configurations for testing.
- Presented quantitative performance metrics and qualitative observations for each test case. Identified areas for improvement. Perform Hyper Parameter Tuning if necessary.

9.3 Performance Measures

1. Root Mean Square Error (RMSE)- A metric called root mean square error (RMSE) is employed in regression analysis to assess the precision of a predictive model. It calculates the average size of the errors between the actual and predicted values. Better accuracy is indicated by a lower RMSE value, which shows that the model's predictions are more accurate relative to the actual values. The formula for RMSE is:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{9.1}$$

   Where:

   N : Number of observations or data points

   y_i : Actual value of the dependent variable for i-th obs

   $\hat{y}_i$: Predicted value of the dependent variable for i-th obs

2. R-squared- A statistical metric called R-squared shows how much of the variation in a regression model is anticipated by the independent variables. Better model fit and more accurate prediction are indicated by a higher value. Regression analysis uses both R-squared and RMSE.
   The formula for R-Squared is:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{9.2}$$

Where:

R^2 : R-squared (Coefficient of Determination)

N : Number of observations or data points

y_i : Actual value of the dependent variable for$i$-th obs

$\hat{y}_i$: Predicted value of the dependent variable for$i$-th obs

$\bar{y}$: Mean of the actual values of the dependent variable

9.4 Results and Comparison

9.4.1 Result Analysis

```
In [90]: Results
Out[90]:
```

	Model	RMSE-Train	R2-Train	RMSE-Test	R2-Test
0	BiLSTM	14.905476	0.801158	14.870198	0.820290
1	BiTRNN	15.054863	0.797152	14.414729	0.831130
2	BiGRU	14.909635	0.801047	14.765987	0.822800
3	ProgNet	15.005557	0.798479	14.961431	0.818078
4	DCNN	15.495105	0.785115	15.453339	0.805919
5	Random Forest (Ensemble)	13.206712	0.843899	14.055435	0.839444

Fig. 9.4.2(a) FD001

```
In [87]: Results
Out[87]:
```

	Model	RMSE-Train	R2-Train	RMSE-Test	R2-Test
0	BiLSTM	12.975082	0.849326	13.294878	0.856349
1	BiTRNN	13.345832	0.840593	13.511217	0.851636
2	BiGRU	12.998959	0.848771	13.078369	0.860990
3	ProgNet	13.990586	0.824818	13.360606	0.854925
4	DCNN	13.175864	0.844627	13.177635	0.858872
5	Random Forest (Ensemble)	11.402315	0.883640	13.223092	0.857896

Fig. 9.4.2(b) FD002

```
In [92]: Results
Out[92]:
```

	Model	RMSE-Train	R2-Train	RMSE-Test	R2-Test
0	BiLSTM	15.041520	0.797512	15.002062	0.817089
1	BiTRNN	15.196477	0.793318	14.934231	0.818739
2	BiGRU	14.973442	0.799340	14.798542	0.822018
3	ProgNet	15.008645	0.798396	15.065643	0.815535
4	DCNN	15.520498	0.784410	15.584509	0.802610
5	Random Forest (Ensemble)	13.426143	0.838668	14.451183	0.830275

Fig. 9.4.2(c) FD003

In [87]: Results

Out[87]:

	Model	RMSE-Train	R2-Train	RMSE-Test	R2-Test
0	BiLSTM	12.978761	0.849241	13.131943	0.859849
1	BiTRNN	13.194022	0.844199	12.889365	0.864979
2	BiGRU	12.942321	0.850086	13.063094	0.861314
3	ProgNet	14.092154	0.822266	13.517677	0.851494
4	DCNN	13.361153	0.840226	13.880117	0.843424
5	Random Forest (Ensemble)	11.388845	0.883915	12.583296	0.871315

Fig. 9.4.2(d) FD004

Table. 9.4.2 Performance Analysis

The report evaluates a predictive maintenance strategy for estimating the Remaining Useful Life (RUL) of turbofan engines using deep learning and machine learning models. The strategy's performance is assessed on four datasets (FD001, FD002, FD003, FD004), with a focus on the Random Forest Regressor's effectiveness.

Results show that the Random Forest Regressor consistently outperforms other models, achieving lower RMSE values and higher R-squared scores across all datasets. For instance, it recorded an RMSE-Test of 14.50 and an R-squared-Test of 0.83 on the FD001 dataset, demonstrating superior accuracy and reliability in predicting RUL.

In contrast, the ProgNet model exhibited poorer performance with lower R-squared scores and higher RMSE values, indicating its inefficacy. Other models like Bi-TRNN, Bi-GRU, Bi-LSTM, and DCNN performed variably, with Bi-LSTM and DCNN excelling in the FD003 dataset but underperforming on FD002 and FD004.

In conclusion, the ensemble approach with the Random Forest Regressor shows significant potential for improving aviation engine maintenance procedures. Its robustness and accuracy make it a valuable tool for predictive maintenance, offering insights that can lead to more effective and efficient maintenance practices.

Chapter 10

Conclusion

RUL Prediction:This study presents a comprehensive approach to predicting the Remaining Useful Life (RUL) of turbofan engines using machine learning and deep learning models. The process starts with preprocessing, feature selection, normalization, followed by model construction and evaluation. The Random Forest Regressor ensemble method is particularly promising, leveraging the strengths of multiple base learners to achieve superior performance in RUL prediction. The ensemble model delivers competitive accuracy, interpretability, and resilience against overfitting, making it a valuable tool for predictive maintenance tasks.The future scope of the research includes implementing advanced techniques, such as Genetic Algorithm, Recursive Feature Elimination, LASSO, FIRF, and AFICv, and integrating real-time sensor data into the predictive maintenance system. The research also envisions extending its methodology and models to broader applications in industrial predictive maintenance, contributing to maintenance practices and operational efficiency.

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Appendix A

Plagiarism Report

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Fig. A.2 Plagiarism Report of Review Paper

Appendix B

Base Paper

- Title: Deep Bidirectional Recurrent Neural Networks Ensemble for Remaining Useful Life Prediction of Aircraft Engine
- Authors: K. Hu, Y. Cheng, J. Wu, H. Zhu, and X. Shao
- Published in: IEEE Transactions on Cybernetics (Volume: 53)
- Publication Year: 2023

Deep Bidirectional Recurrent Neural Networks Ensemble for Remaining Useful Life Prediction of Aircraft Engine

Kui Hu, Yiwei Cheng, Jun Wu, *Member, IEEE*, Haiping Zhu, and Xinyu Shao

***Abstract*—Remaining useful life (RUL) prediction of aircraft engine (AE) is of great importance to improve its reliability and availability, and reduce its maintenance costs. This article proposes a novel deep bidirectional recurrent neural networks (DBRNNs) ensemble method for the RUL prediction of the AEs. In this method, several kinds of DBRNNs with different neuron structures are built to extract hidden features from sensory data. A new customized loss function is designed to evaluate the performance of the DBRNNs, and a series of the RUL values is obtained. Then, these RUL values are reencapsulated into a predicted RUL domain. By updating the weights of elements in the domain, multiple regression decision tree (RDT) models are trained iteratively. These models integrate the predicted results of different DBRNNs to realize the final RUL prognostics with high accuracy. The proposed method is validated by using C-MAPSS datasets from NASA. The experimental results show that the proposed method has achieved more superior performance compared with other existing methods.**

***Index Terms*—Aircraft engine (AE), bidirectional recurrent neural networks (BDRNNs), deep learning, ensemble learning (EL), prognostics and health management (PHM), remaining useful life.**

I. Introduction

AIRCRAFT engine (AE) is a core part of various kinds of airplanes, and its reliability is very important to ensure the safety of the aircraft [1], [2]. To improve the reliability and availability of the AE and reduce its maintenance costs, prognostics and health management (PHM) has become a research hotspot in the field of the AE recently. PHM of the AE involves analyzing the data acquired by various types of sensors, using the artificial intelligence (AI) algorithm to evaluate health status, forecast the failure before the AE breaks down, and providing a series of maintenance suggestions combined with the existing resource. As an important part of PHM, a well-designed remaining useful life (RUL) prediction method can help engineers arrange maintenance and repairing periodicity of the AE reasonably, which effectively prevents its performance degradation or even catastrophic failure [3]–[6].

In recent years, RUL prediction methods based on AI and big data mining have attracted a wide range of attention. Those methods mainly focus on finding the mapping relationship between massive monitoring data and the corresponding RUL label by using advanced machine learning algorithms. The machine learning algorithms, including artificial neural networks [7], support vector machine (SVM) [8], hidden Markov model [9], etc., are suitable for inferring hidden correlation and causality from monitoring data and learning degradation trend. However, these sophisticated machine learning methods still have some shortcomings.

1) Most machine learning algorithms can only calculate the output according to the current input data [10]. However, in industrial applications, the degradation process occurs in the entire life cycle. The correlations of sequence data at different times will affect the prediction accuracy of the model. Therefore, an algorithm that can capture the time dependence in sequence data for RUL prediction has a very broad prospect.
2) Due to the changing operating environment and working modes, a single machine learning algorithm usually has some limitations in extracting features and fitting curves. It means that the trained machine learning model only has high accuracy in a certain situation and might not work well in other situations.

To overcome the shortcomings mentioned above, a new deep bidirectional recurrent neural networks (DBRNNs) ensemble method is proposed in this article for accurate and robust RUL prediction of the AEs. In this method, multiple bidirectional recurrent neural networks (RNNs) are introduced to capture and mine features, which could utilize information from sequence data in forward and backward directions to capture long-term dependencies. Besides, ensemble learning (EL) is considered as a good cut-in point to increase the robustness of the built model. By integrating several DBRNN models under different conditions using multiple regression decision

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tree (RDT) models, the generalization of the proposed method and its prediction accuracy under different conditions might be improved.

The main contributions of this article are summarized as the following three points.

1) A novel DBRNN ensemble prognostic model is proposed, which contains two major parts. One is that three kinds of the DBRNNs with different structures are introduced to extract hidden features from monitoring data. Each DBRNN model collects information from both forward and backward data sequences for prediction, which increases data perception ability of the model. The other is that an ensemble model integrating multiple networks is built to improve the overall prediction accuracy and generalization performance.
2) An RDT-based multiple model ensemble algorithm is proposed to fuse prediction values of multiple DBRNNs and infer optimal RUL by the weighted summation of multiple RDT models trained iteratively. Meanwhile, a new customized loss function is designed to evaluate the deviation degree of the DBRNN models. It punishes the later prediction more than the early prediction so as to reduce the accident risk caused by the prediction errors.
3) Key factors, including the number of hidden neurons, the maximum depth, and the number of iterations on RDT, are studied thoroughly. The experimental results demonstrate the superiority of the proposed method to realize accurate RUL prediction of AEs under various operating conditions and failure modes, and the power of combining the EL and deep learning for the RUL prediction of complex dynamical systems.

The remainder of this article is organized as follows. Section II reviews the concept and literatures related to RUL prediction, RNNs, and EL. Section III describes the proposed DBRNN ensemble method in detail. Section IV presents the general process of DBRNN ensemble-based RUL prediction. Section V evaluates the performance of the proposed method. Finally, Section VI draws the conclusion and introduces the future research.

II. Related Works

A. Remaining Useful Life Prediction

RUL prediction is a critical part of PHM [11], [12], which deduces the RUL of equipment in the operating environment by analyzing the health status and degradation trend of the equipment. The entire life cycle process of the equipment from health to failure generally contains three states: 1) normal operation state; 2) degradation state; and 3) failure state. It is noted that the fault of the equipment does not occur instantaneously, but gradually aggravates over time. The performance of the equipment is degraded by the factors, such as the working environment and fatigue aging of the equipment itself, which ultimately leads to the failure of the equipment [13], [14]. At the same time, the RUL of the equipment can be predicted by the degree of performance degradation of the equipment.

According to the literature [15], the RUL prediction methods are classified into three types, that is: 1) model-based method; 2) data-driven method; and 3) hybrid method. Among them, the data-driven prognostic method does not need priori knowledge of the equipment failure mechanism. It only analyzes the health features hidden in the monitoring data reflecting the changes in the health state over time and completes the RUL prediction. Thus, data-driven prognostic methods have attracted wide attention.

Many data-driven RUL prognostic methods have been reported to achieve good results for different equipment. Ahmad *et al.* [16] proposed a hybrid forecasting technology for rolling bearings based on regression adaptive predictive models to learn the evolving trend of the health indicators and used these models to predict the RUL. Li *et al.* [17] constructed a deep convolution neural network (DCNN) model for RUL prediction where the raw sensor sequence data are standardized as the input and the RUL value of the label are fitted. In general, monitoring data used in these methods are typical time series that collect and record health status of the equipment in time sequence. To some extent, it is hard for the methods mentioned above to correlate data at different times. Luckily, it is found that the RNNs have a unique structure to memorize data and correlate data at different times.

B. Recurrent Neural Networks

RNN is a kind of neural network that includes feedforward connection and internal feedback connection [18], [19]. Because of its special network structure, RNN can extract useful information from the previously processed data across time steps and fuse them into the current process. RNN shows a strong advantage in dealing with time series. Many literatures show that RNN-based RUL prediction method has been widely used [20]. Heimes [21] used the RNN structure to realize the RUL prediction. The model was trained by an extended Kalman filter method. The experiments show that the performance of the proposed method is significantly better than that of the multilayer perceptron (MLP)-based method. However, traditional RNN (TRNN) usually faces the problem of memory loss. This is because it has no structure to control memory flow in the circulation layer. There will be a large prediction bias when dealing with long time monitoring sequence.

LSTM [22] and GRU [23] are the improvements of TRNN. These two kinds of neural networks construct unique "gate" structures, which determine the information characteristics passed under the optimal conditions. Zhang *et al.* [24] proposed a lithium battery RUL prediction model based on LSTM, which solved the problem of long-term dependence of degradation data.

The RNN-based RUL prediction method not only improves the accuracy of RUL prediction but also has the characteristics of fast convergence rate and high stability. It plays an important role in the field of reliability evaluation and RUL prediction [25], [26]. Although researchers have been working to improve the structure of TRNN to avoid the problem of gradient disappearance or explosion, it is still necessary

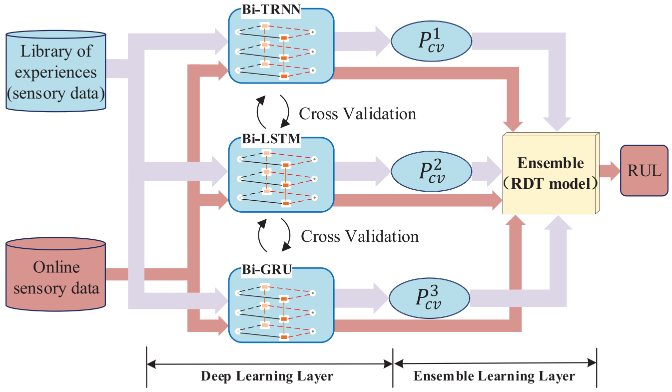

Fig. 1. Architecture of the DBRNN ensemble method.

to improve its robustness and accuracy by methods such as EL.

C. Ensemble Learning

It is rarely possible that a single machine learning model consistently performs well in different applications [27]. An EL method that integrates multiple base learners often shows higher accuracy and better generalization [28]. There are two main steps contained in the EL method. One is to generate base learners, and the other is to design a combination strategy to integrate the results of these base learners. In order to ensure high accuracy and generalization of the EL method, base learners are usually required to have enough diversity and generate smaller errors. Besides, a good ensemble strategy has the ability of integrating the results of different base learners so as to obtain better prediction performance than any ensemble member.

The application of EL in RUL prediction has become a research hotspot recently [29]. Rigamonti *et al.* [30] constructed an ensemble echo state networks model for enhancing the performances of the individual networks and providing an estimation of the uncertainty affecting the RUL prediction. Kordestani *et al.* [31] developed an integrated method using an artificial neural network and discrete wavelet transform is via ordered weighted averaging operator to diagnose faults of aircrafts' multifunctional spoiler.

III. Deep Bidirectional Recurrent Neural Networks Ensemble

Some EL methods, such as random forest and adaboost, have the inevitable drawbacks. For example, the random forest tends to cause the overfitting problem in the classification or regression task affected by complex noise [32], and the adaboost is only applied to the classification task [33]. Therefore, the two methods are not suitable for RUL prediction of AE. To solve this problem, a DBRNN ensemble method is proposed, which is revealed in Fig. 1.

As shown in Fig. 1, the proposed DBRNN ensemble method consists of two layers, that is: 1) deep learning layer and 2) EL layer. In the deep learning layer, three kinds of the DBRNNs with different neuron structures are built and their network parameters are determined by backpropagation through the time algorithm and cross-validation method. In the EL layer, the predicted results obtained by the three DBRNN models are reencapsulated. Multiple RDT models are built to relearn the results iteratively. According to the accuracy of the RDT models, the relearned results are weighted and summed to realize the final RUL prediction.

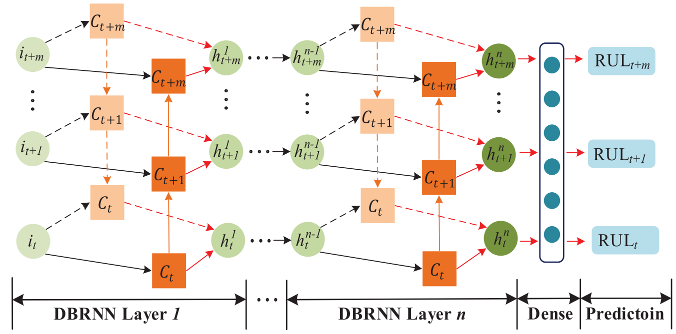

Fig. 2. Structure of DBRNN.

A. Deep Learning Layer

In the deep learning layer, individual ensemble members are constructed as base learners to realize preliminary RUL predictions of AE. The choice of ensemble members is an important issue. Most intelligent models only establish the mapping relationship between the inputs and RUL at a certain time, which ignores the temporal dependency in the monitoring signals. However, the RUL prediction is a typical time-series problem, which means the predicted output is not only related to the current input but also affected by various factors throughout the entire life range. To capture the temporal dependency in the monitoring signals and increase the diversity of ensemble members, three different kinds of DBRNN models are constructed as individual ensemble members. In the proposed method, three specific DRNN structures, including TRNN, LSTM, and GRU, are adopted. Herein, the TRNN mainly focuses on extracting features in adjacent or close-to-distance data. The LSTM is specially designed to deal with long-term dependency, which extracts features from long-span sequence data. GRU can obtain valuable hidden data features by the unique "update gate" structure, which makes the feature extracted by GRU different from that of LSTM. Based on their different characteristics, these three structures are chosen to learn and mine data features from different aspects.

Fig. 2 shows the structure of the DBRNN models. In this structure, the inputs (i.e., $\boldsymbol{i}_t = [i_{t_1}, i_{t_2}, \ldots, i_{t_m}]$) are fed into the RNN cell (i.e., $\boldsymbol{C}_t$) according to the succession sequence, and the hidden state of the current layer is obtained and prepared to be fed into the next BRNN layer. After being processed by the dense layer, the RUL prediction of the base learner is finally obtained. These DBRNNs can continuously iterate and update the hidden state of cells in the time dimension to achieve the flow and in-depth utilization of information in a large time span. The cell structures of different RNNs are shown in Fig. 3.

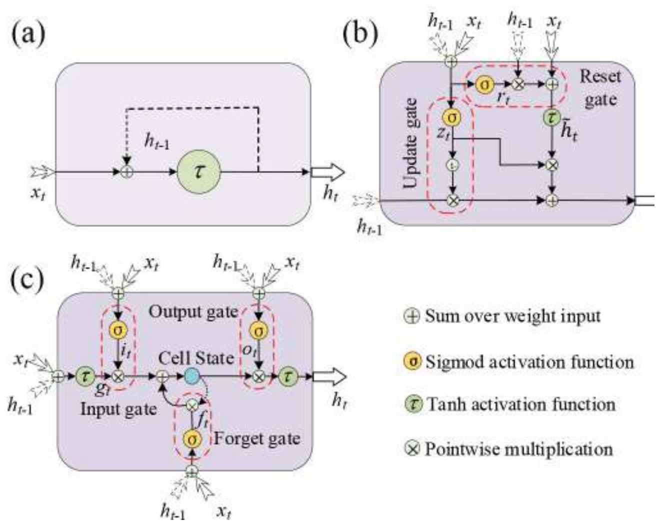

Fig. 3. Cell frame of the DBRNNs. (a) TRNN cell. (b) GRU cell. (c) LSTM cell.

As mentioned above, three types of neurons are adopted to ensure the diversity of the models and make it possible for the models to capture and mine data features from different aspects. The information flow in the TRNN neuron, GRU neuron, and LSTM neuron is shown in Fig. 3(a)–(c), respectively. As shown in Fig. 3(a), the current input is concentrated with the previous hidden state h_{t-1}^{TRNN}, and then fed to the activation function operation to generate a new hidden state h_t^{TRNN}, which means that it could extract information from the input of the previous cell state. The computational process in the TRNN neuron at t time is, respectively, described as

$$\begin{aligned}\boldsymbol{h}_t^{\text{TRNN}} &= \mathbb{H}^{(R)}\left(\boldsymbol{h}_{t-1}^{\text{TRNN}}, \boldsymbol{x}_t, \boldsymbol{\theta}_{\text{TRNN}}\right)\\ &= \tau\left(\boldsymbol{W}_t \cdot \left[\boldsymbol{h}_{t-1}^{\text{TRNN}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_t\right)\end{aligned} \tag{1}$$

where $\mathbb{H}^{(R)}$ defines a nonlinear transformation function in TRNN neuron. θ_{TRNN} is a parameter set of TRNN neurons, respectively. x_t denotes the current input. $\boldsymbol{W}_t$ are weights of the current input x_t and the recurrent input h_{t-1}, and b_t are bias weights of the corresponding node. $\tau(\cdot)$ denotes the tanh function.

Fig. 3(b) shows the structure of the GRU neurons, in which the reset gate determines the output proportion of the new cell state in the previous time, and the update gate determines the output proportion of the new cell state in the current time.

It is seen from Fig. 3(c) that each LSTM neuron has three well-designed structures, including: 1) input gate; 2) forget gate; and 3) output gate. The input gate determines what cell state needs to be updated. The forget gate decides what information will be thrown away from the previous cell state. The output gate resolves which part of the cell state will be exported out of the cells. The computational process in the GRU neuron and the LSTM neuron at t time is, respectively, described as

$$\begin{aligned}\boldsymbol{h}_t^{\text{GRU}} &= \mathbb{H}^{(G)}\left(\boldsymbol{h}_{t-1}^{\text{GRU}}, \boldsymbol{x}_t, \boldsymbol{\theta}_{\text{GRU}}\right)\\ &= \begin{cases} z_t = \sigma\left(\boldsymbol{W}_z \cdot \left[\boldsymbol{h}_{t-1}^{\text{GRU}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_z\right)\\ \mathbf{r}_t = \sigma\left(\boldsymbol{W}_r \cdot \left[\boldsymbol{h}_{t-1}^{\text{GRU}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_r\right)\\ \widetilde{\boldsymbol{h}}_t = \tau\left(\boldsymbol{W}_h \cdot \left[\mathbf{r}_t * \boldsymbol{h}_{t-1}^{\text{GRU}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_h\right)\\ \boldsymbol{h}_t^{\text{GRU}} = (1 - z_t) * \boldsymbol{h}_{t-1}^{\text{GRU}} + z_t * \widetilde{\boldsymbol{h}}_t \end{cases}\end{aligned} \tag{2}$$

$$\begin{aligned}\boldsymbol{h}_t^{\text{LSTM}} &= \mathbb{H}^{(L)}\left(\boldsymbol{h}_{t-1}^{\text{LSTM}}, x_t, \theta_{\text{LSTM}}\right)\\ &= \begin{cases} \boldsymbol{g}_t = \tau\left(\boldsymbol{W}_g \cdot \left[\boldsymbol{h}_{t-1}^{\text{LSTM}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_g\right)\\ \boldsymbol{i}_t = \sigma\left(\boldsymbol{W}_i \cdot \left[\boldsymbol{h}_{t-1}^{\text{LSTM}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_i\right)\\ \boldsymbol{f}_t = \sigma\left(\boldsymbol{W}_f \cdot \left[\boldsymbol{h}_{t-1}^{\text{LSTM}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_f\right)\\ \boldsymbol{C}_t = \boldsymbol{C}_{t-1} * \boldsymbol{f}_t + \boldsymbol{g}_t * \boldsymbol{i}_t\\ \boldsymbol{o}_t = \sigma\left(\boldsymbol{W}_o \cdot \left[\boldsymbol{h}_{t-1}^{\text{LSTM}}, \boldsymbol{x}_t\right] + \boldsymbol{b}_o\right)\\ \boldsymbol{h}_t^{\text{LSTM}} = \boldsymbol{o}_t * \tau(\boldsymbol{C}_t) \end{cases}\end{aligned} \tag{3}$$

where $\mathbb{H}^{(G)}$ and $\mathbb{H}^{(G)}$ are nonlinear transformation functions in GRU neuron and LSTM neuron, respectively. $\boldsymbol{\theta}_{\text{GRU}}$ and $\boldsymbol{\theta}_{\text{LSTM}}$ are parameter sets of three kinds of the neurons, respectively. $\boldsymbol{x}_t$ denotes the current input. $\boldsymbol{h}_{t-1}^{\text{GRU}}$ and $\boldsymbol{h}_{t-1}^{\text{LSTM}}$ are the outputs of TRNN neurons, GRU neurons, and LSTM neurons at $t-1$ time, respectively. $\boldsymbol{W}_z$, $\boldsymbol{W}_r$, $\boldsymbol{W}_{\boldsymbol{h}}$, $\boldsymbol{W}_g$, $\boldsymbol{W}_i$, $\boldsymbol{W}_f$, and $\boldsymbol{W}_o$ are weights of the current input x_t and the recurrent input $\boldsymbol{h}_{t-1}$. $\boldsymbol{b}_z$, $\boldsymbol{b}_r$, $\boldsymbol{b}_h$, $\boldsymbol{b}_g$, $\boldsymbol{b}_i$, $\boldsymbol{b}_f$, and $\boldsymbol{b}_o$ are bias weights of the corresponding node. σ represents the sigmoid function, and $*$ denotes the pointwise multiplication. $\boldsymbol{z}_t$ and $\boldsymbol{r}_t$ are the output of the update gate and reset gate of the GRU cell unit. For the LSTM cell unit, $\boldsymbol{g}_t$, $\boldsymbol{i}_t$, $\boldsymbol{f}_t$, and $\boldsymbol{o}_t$ are the input node, input gate, output of the forget gate, and output gate, respectively. $\boldsymbol{C}_t$ and $\boldsymbol{C}_{t-1}$ are the cell state values at time t and $t-1$, respectively.

During the training process of the DBRNN models, the output is the connection vectors of the forward and backward processes. The output $h_t^{(*)}$ is computed as

$$\boldsymbol{h}_t^{(*)} = \overset{\rightharpoonup}{\boldsymbol{h}}_t^{(*)} \oplus \overset{\leftharpoonup}{\boldsymbol{h}}_t^{(*)} \tag{4}$$

where $\rightharpoonup$ and $\leftharpoonup$ denote the forward and backward processes, respectively, and $*$ can be replaced by TRNN, GRU, and LSTM. The operator $\oplus$ represents the elementwise sum of the outputs of the forward and backward processes. The corresponding hidden vectors are updated as

$$\overset{\rightharpoonup}{\boldsymbol{h}}_t^{(*)} = \mathbb{H}^{(*)}\left(\boldsymbol{x}_t^{(*)}, \boldsymbol{h}_{t-1}^{(*)}, \boldsymbol{\theta}_{(*)}\right) \tag{5}$$

$$\overset{\leftharpoonup}{\boldsymbol{h}}_t^{(*)} = \mathbb{H}^{(*)}\left(\boldsymbol{x}_t^{(*)}, \boldsymbol{h}_{t+1}^{(*)}, \boldsymbol{\theta}_{(*)}\right) \tag{6}$$

where $\mathbb{H}^{(*)}$ is the transition functions in hidden units of three types of the neurons, which is defined by formulas (1)–(3). The proposed DBRNN model consists of the input layer, hidden cell layer, and output layer. The input layer receives the AE sensor signals. After deep mining of multihidden cell layers, the input data are finally processed through a full connection layer to obtain the output results. Under the action of the activation function, the predicted RUL is obtained. This process is defined as

$$o_i = \varphi\left(\boldsymbol{W}_i \boldsymbol{h}_t^{(*)} + \boldsymbol{b}_i\right) \tag{7}$$

where o_i denotes the final output RUL value and φ represents the activation function.

A variety of DBRNN models with different cell structures is utilized to improve the diversity of ensemble members and enhance the generalization of the ensemble model. Meanwhile, the cross-validation technique is adopted to avoid the overfitting of these individual ensemble members [34]. Fig. 4 shows the process of three-fold cross-validation. The sensory dataset of AE is divided into two parts, that is: 1) a subtraining

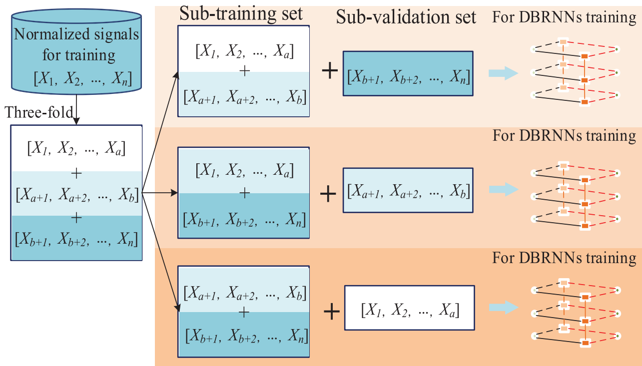

Fig. 4. Three-folds cross validation process.

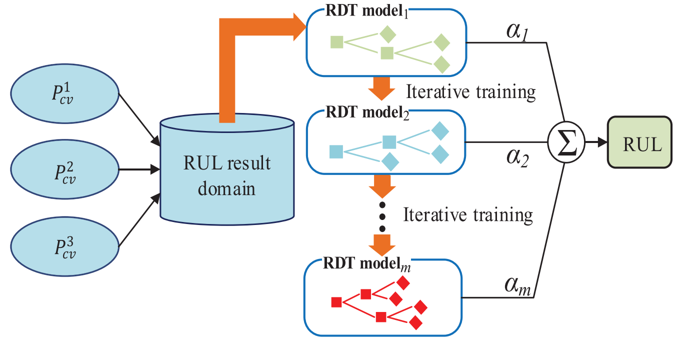

Fig. 5. Specific steps for RDT-based EL.

set and 2) a subvalidation set. $[\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_n]$ represent the sensory data of n AEs where $\boldsymbol{X}_i = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_t]$ are the signals sequences, and x_t denotes the multisensory data vector at cycle t. The DBRNN models will undergo three training sessions, in which two-thirds of the AE data are selected for training models and the rest for model validation without repeating in each training session. Taking the first training sessions as an example, the first and second fold of the sensory data, that is, $[\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_a]$ and $[\boldsymbol{X}_{a+1}, \boldsymbol{X}_{a+2}, \ldots, \boldsymbol{X}_b]$, are fed into the DBRNN models for training, and the third fold of the sensory data $[\boldsymbol{X}_{b+1}, \boldsymbol{X}_{b+2}, \ldots, \boldsymbol{X}_n])$ is used for validation, where $a = 1/3n$ and $b = 2/3n$.

The neural network updates the parameters by seeking the partial derivative of the network parameters. The optimization algorithm of the parameters will directly affect the training efficiency and convergence of the DBRNN model. For the traditional optimization algorithm such as stochastic gradient descent (SGD), the learning rate (LR) is fixed during the network training process, which means the LR value is particularly critical. A small LR will lead to slow convergence while a large LR will cause oscillations and fail to converge to the optimal solution [35]. To avoid this problem, a new algorithm called adaptive moment estimation (Adam) is used to optimize the parameters in the deep learning layer of the DBRNN. The Adam algorithm designs an independent adaptive LR for different parameters by analyzing the first moment estimation (FME) and second moment estimation (SME) of the gradient. Therefore, by constraining the global LR, the Adam algorithm has good stability, consumes less configuration resources while ensuring convergence, and does not need to store all global gradients, which is very suitable for processing large-scale data. The updating process of network parameters by the Adam algorithm is expressed as

$$\boldsymbol{g}_t = \nabla_\theta \sum_i L(\boldsymbol{\theta}_{t-1}) \tag{8}$$

$$\boldsymbol{m}_t = \boldsymbol{\lambda}_1 \boldsymbol{m}_{t-1} + (\mathbf{1} - \boldsymbol{\lambda}_1)\boldsymbol{g}_t \tag{9}$$

$$\boldsymbol{n}_t = \boldsymbol{\lambda}_2 \boldsymbol{n}_{t-1} + (\mathbf{1} - \boldsymbol{\lambda}_2)\boldsymbol{g}_t^2 \tag{10}$$

$$\overline{\boldsymbol{m}}_t = \frac{\boldsymbol{m}_t}{\mathbf{1} - \boldsymbol{\lambda}_1^t} \tag{11}$$

$$\overline{\boldsymbol{n}}_t = \frac{\boldsymbol{n}_t}{\mathbf{1} - \boldsymbol{\lambda}_2^t} \tag{12}$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} - \boldsymbol{\omega} \frac{\overline{\boldsymbol{m}}_t}{\sqrt{\overline{\boldsymbol{n}}_t} + \epsilon} \boldsymbol{g}_t \tag{13}$$

where $\boldsymbol{g}_t$ indicates the gradient of the loss function $L(\boldsymbol{\theta})$ to the network parameter set $\boldsymbol{\theta}$. $\boldsymbol{m}_t$ and $\boldsymbol{n}_t$ represent the FME and SME of gradient, respectively. $\overline{\boldsymbol{m}}_t$ and $\overline{\boldsymbol{n}}_t$ are deviation corrections for $\boldsymbol{m}_t$ and $\boldsymbol{n}_t$, respectively. $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ represent decay rates of FME and SME, respectively. ω denotes the step size and ϵ is the numerical stability constant. $\boldsymbol{\theta}_{t-1}$ is the calculated renewal value of $\boldsymbol{\theta}_t$ at $t-1$ time.

B. Ensemble Learning Layer

In the EL layer, a novel RDT-based method is proposed to integrate the predicted RUL results obtained by the DBRNN models so as to mine the potential characteristics of monitoring signals more comprehensively and achieve a more accurate RUL prediction. The RDT model proposed by Breiman *et al.* [36] has been widely used in the field of statistics and data mining. It uses a completely different way from traditional statistics to build prediction criteria. It is given in the form of the binary tree, which is easy to understand, use, and explain. In many cases, the RDT model is more accurate than the algebra prediction criterion constructed by common statistical methods [37].

By iteratively training multiple RDT models, the predicted RUL results are relearned, and the weights are allocated according to the training errors of the models. After summing up the weighted RUL results, the final RUL prediction is completed.

Fig. 5 indicates the process of the EL, which includes three steps. In the first step, the predicted results of the three DBRNN models are reencapsulated into a new RUL domain $\boldsymbol{X}_o$. In the second step, multiple RDT models are set up and iteratively trained by using the new RUL domain $\boldsymbol{X}_o$. The weight of each model will be updated during the training process. In the third step, the predicted results of each RDT model are integrated with the corresponding weights of the model to realize the final RUL prediction.

Each RDT model divides the input domain into several units, each of which has a corresponding output. The goal of training the RDT model is to find an accurate space partition and obtain the accurate mapping relationship between the partition unit and the output results. When the input characteristics are classified into a certain unit, the corresponding output value will be obtained. The computational procedure is described as

$$\mathbb{T}_m(\boldsymbol{x}_i) = \begin{cases} (j,s) = \min_{j,s}\big[\min_{c_1} \text{Loss}(y_i, c_1) \\ \qquad\qquad +\ \min_{c_2} \text{Loss}(y_i, c_2)\big] \\ \boldsymbol{R}_k(j,s) = \big\{\boldsymbol{x} \mid x^j \le s\big\} \\ \boldsymbol{R}_{k+1}(j,s) = \big\{\boldsymbol{x} \mid x^j \ge s\big\} \\ \widehat{c}_k = \frac{1}{N_k}\sum_{x_i \in R_k} y_i,\ \ x_i \in \boldsymbol{R}_k \\ f(x_i) = \sum_{k=1}^{K} \widehat{c}_m I(x_i \in \boldsymbol{R}_k) \end{cases} \tag{14}$$

where $\mathbb{T}_m$ is the mth RDT model of iterative training. j and s refer to the splitting variable and splitting point, respectively. R_k is the partition of domain, $\widehat{c}_k$ denotes the output value of the kth partition of domain R_k, and $\widehat{c}_m$ denotes the average of all the y_i values in the partition R_k. $f(\cdot)$ represents the final output, which is a piecewise function.

In the iterative training process, all training samples are given the same initial weight $\boldsymbol{W}_1 = (w_1^1, w_1^2, \ldots, w_1^n)$, $w_1^i = (1/n)$, $i = 1, 2, \ldots, n$. Then, the first RDT model $\mathbb{T}_1$ is trained. The error rate α_m of the decision tree model is calculated, and the weight coefficient of $\mathbb{T}_1$ is calculated by the error rate, and the weight distribution of the training samples $\boldsymbol{W}_2$ for the next iterative training is updated. Then, a new round of training is started. The training process stops after reaching the maximum number of iterations M, and finally, obtain m RDT models $\{\mathbb{T}_1, \mathbb{T}_2, \ldots, \mathbb{T}_m\}$ and their corresponding weight coefficients $\{\alpha_1, \alpha_2, \ldots, \alpha_m\}$. Finally, the linear combination of the prediction results of these RDT models is linearly combined to obtain the final RUL prediction. The description of the RDT-based DBRNNs EL is shown in Algorithm 1.

Algorithm 1 RDT-Based DBRNNs EL

Input:
Training dataset $\mathcal{T} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, while $x_i \in X_0$, $y_i \in RUL$, $i = 1, 2, \ldots, n$
M: Maximum number of iterative training
Output:
Trained *RDT*s $= \{\mathbb{T}_1, \mathbb{T}_2, \ldots, \mathbb{T}_m\}$
Step 1) Initialization:
Generate a weight distribution of initial training data:

$$\boldsymbol{W}_1 = \left(w_1^1, w_1^2, \ldots, w_1^n\right),\ \ w_1^i = \frac{1}{n}, i = 1, 2, \ldots, n$$

Step 2) Iterative training:
for $m = 1, 2, \ldots, M$ do
Step 2.1) Train an *RDT* model $\mathbb{T}_m$ using a dataset with the weight distribution W_1.
Step 2.2) Calculate the maximum error of the model $\mathbb{T}_m$

$$E_m = |y_i - \mathbb{T}_m(x_i)|$$

Step 2.3) Calculate the relative error of each RUL training sample:

$$e_m^i = 1 - exp(\frac{-y_i + \mathbb{T}_m(x_i)}{E_m})$$

Step 2.4) Calculate the error rate:

$$e_m = \sum_{i=1}^{n} e_m^i w_m^i$$

Step 2.5) Calculate the weight coefficient of the model $\mathbb{T}_m$

$$\alpha_m = \frac{e_m}{1 - e_m}$$

Step 2.6) Update the weight distribution of the training data:

$$w_{m+1}^i = \frac{w_m^i}{\sum_{i=1}^n w_m^i \alpha_m^{1-e_m^i}} \alpha_m^{1-e_m^i}$$

end for
Step 3) Integration:
Construct a linear combination of the trained *RDT*s according to the calculated weights:

$$RUL(x) = \sum_{m=1}^{M} (ln\frac{1}{\alpha_m})\alpha_m \mathbb{T}_m(x)$$

IV. General Procedure of the Proposed Method

The procedure of the DBRNN ensemble-based RUL prediction consists of two stages, that is: 1) offline modeling and 2) online prediction, which are detailed in Table I. In the procedure, data preprocessing, parameter optimization, and loss function are indispensable.

A. Data Preprocessing

In general, the monitoring data collected by sensors often have different scales and orders of magnitude. A normalization method is adopted to improve the convergence speed and fitting accuracy of the models, which is expressed as

$$\text{Norm}\left(x^{(s,c)}\right) = \frac{x - x_{\min}^{(s,c)}}{x_{\max}^{(s,c)} - x_{\min}^{(s,c)}} \tag{15}$$

where s denotes each kind of sensors and c denotes different operating conditions, and $x_{\min}^{(s,c)}$ and $x_{\max}^{(s,c)}$ are the minimum and maximum values of the sensor signals corresponding to the operation condition c and sensor s.

Since the background noise is unavoidable in data acquisition, the Savitzky–Golay convolution smoothing algorithm is used to reduce the background noise, which is given as

$$\overline{x_k} = \frac{1}{H}\sum_{i=-w}^{+w} x_{k+i} h_i \tag{16}$$

where $\overline{x_k}$ denotes a smooth value at the kth point, and h_i is a smoothing coefficient. H is a smooth window, and $[-w, +w]$ represents the width of windows. The least squares method is used to calculate (h_i/H) by polynomial fitting.

In addition, correlation represents the degree of association between variables. Monotonicity represents the trend of the data degradation over time [38]. In this article, monotonic and correlational analyses are implemented to find the degradation trend and correlation hidden in sensor data, which are expressed as

$$r = \frac{\left|\left(n\sum_n f(t)t - \sum_n f(t)\sum_n t\right)\right|}{\sqrt{\left[n\sum_n f(t)^2 - \left(\sum_n f(t)\right)^2\right]\left[n\sum_n t^2 - \left(\sum_n t\right)^2\right]}} \tag{17}$$

$$m = \frac{\left|\sum_n \sigma(f(t+1) - f(t)) - \sum_n \sigma(f(t) - f(t+1))\right|}{n-1} \tag{18}$$

where r and m represent correlation and monotonicity, respectively. $\sigma(\cdot)$ represents the sign function. n indicates the quantity of the signals.

TABLE I
DESCRIPTION OF THE PROPOSED METHOD

Offline modelling stage	
Step 1:	Sensor data of the AE in the whole life cycle are collected, selected and preprocessed. These data and their corresponding RUL labels constitute the training set for the next training process, that is, $T = \{(x_1, RUL_1), (x_2, RUL_2), \ldots, (x_n, RUL_n)\}$.
Step 2:	The deep learning layer and ensemble learning layer in the DBRNN ensemble method are constructed and relevant parameters are optimized.
Step 3:	The training datasets after three-folds cross-validation are used to train the DBRNN models with back propagation through time algorithm and a unique loss function is designed to evaluate the training error.
Step 4:	The validation datasets are inputted into the trained DBRNN models to obtain the corresponding RUL values.
Step 5:	The predicted results of the DBRNN models are re-encapsulated into the predicted RUL domain $\boldsymbol{X}_o$, which is used for iteratively training multiple RDT models.
Step 6:	Combine all the trained RDT models to establish an ensemble model. The weights of the RDTs are assigned according to the accuracy.
Online prediction stage	
Step 1:	Real-time monitoring data of the AE related sensors is collected. The raw signal is then normalized and smoothed according to formulas (15) and (16).
Step 2:	The preprocessed monitoring data is fed into the well trained DBRNN models to get the predicted results in deep learning layer.
Step 3:	The results are re-encapsulated and put into the ensemble layer to obtain the final RUL predictions by summing the results of the RDT models with assigned weights.

B. Parameters Optimization of DBRNN Ensemble

As is known, different parameter selection might lead to great changes in the structure and complexity of the model. The parameter optimization of the model may help select the model with appropriate complexity, effectively reduce the test error, and improve the generalization of the model.

In the proposed DBRNN ensemble method, multiple hyperparameters, including the number of hidden cell layers and hidden neurons in cell layers, need be adjusted, while the max depth and the iteration numbers of the RDT models in the EL layer also need be confirmed.

In this article, a grid search algorithm is adopted for the optimum hyperparameters of the DBRNN ensemble method. The principle of the grid search is to divide the interval of each parameter value into a series of small intervals, and calculate the target value (usually error) determined by the combination of the corresponding parameter values in order, and select the best one by one so as to obtain the minimum target value and the corresponding optimal parameter value in the interval. For different datasets, the optimal training depth has a significant difference, which is mainly due to the difference in data volume and hidden features of different datasets. This method can ensure that the obtained search solution is globally optimal or near optimal, and avoid significant errors [39].

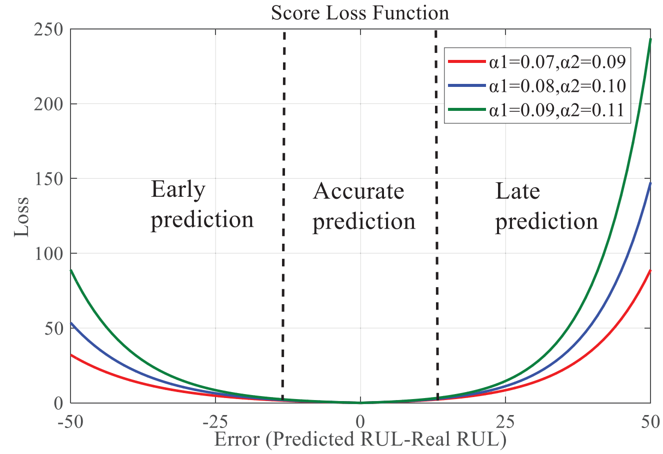

Fig. 6. SLF curve.

C. Loss Function for DBRNNs Training

The loss function evaluates the difference between the actual value and the output value of the model in the iterative training process [45]. The network is trained by minimizing the error between the output and the actual RUL in the training data. Conventional loss functions [such as the mean square error (MSE) and MAE functions] are usually symmetrical, which means that the evaluation values of early prediction and late prediction are the same.

The main goal of RUL prediction is to predict the failure before it occurs to avoid unnecessary downtime and additional maintenance costs. The symmetric loss function is not sensitive to the early and late predictions of the engine, which make it unsuitable for industrial application scenarios. In this article, a novel asymmetric loss function called the score loss function (SLF) is designed to train the DBRNN models, which is expressed as

$$\mathrm{SLF}(Y, f(X)) = \begin{cases} \exp(\alpha_1 |Y - f(X)|) & -1 \;\; Y - f(X) < 0 \\ \exp(\alpha_2 |Y - f(X)|) & -1 \;\; Y - f(X) \geq 0 \end{cases}$$
$$\alpha_1, \alpha_2 \in [0, 1] \tag{19}$$

where Y and $f(X)$ represent actual RUL label and the output RUL value, respectively. $|Y - f(X)|$ denotes the deviation between the predicted value and the actual value. α_1 and α_2 are penalty factors for advanced prediction, and $\alpha_1 < \alpha_2$.

Fig. 6 shows the SLF curve. It can be seen that the SLF will penalize the later prediction more than early prediction, for the later prediction is regarded as the unsafe prediction. In addition, as the factors α_1 and α_2 decrease, the penalty will increase, which is beneficial for early prediction rather than later prediction.

V. Experimental Study

A. Dataset Description

To validate the effectiveness of the proposed RUL prediction method, the dataset generated from the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) test bed is used [26]. The C-MAPSS dataset consists of four sub-datasets. As shown in Table II, operating conditions and failure

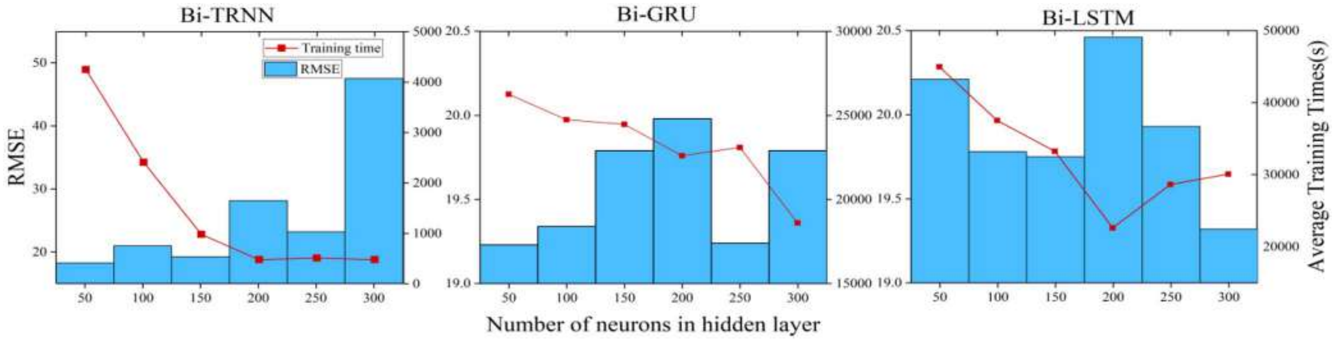

Fig. 7. Prognostic performance of different neuron numbers on FD001.

TABLE II
DATASET DETAILS

Dataset	Training engine	Testing engine	Operating condition	Failure mode
FD001	100	100	1	1
FD002	260	259	6	1
FD003	100	100	1	2
FD004	248	249	6	2

modes of four subdatasets are various. A certain number of training engines and testing engines are included in each subdataset.

Each subdataset consists of monitoring signals acquired from a series of the training engines and the testing engines. These signals are collected by 21 sensors under different operating conditions, including sea-level temperature, Mach number, and altitudes. Different operating conditions have a great impact on the monitoring signals of the sensors. Each engine runs in a healthy state at an early stage, and its performance decreases over time until the engine breaks down. Each engine corresponds to a series of data points sampled by 21 sensors in a life cycle. In the training process, all the training engines are used to train the DBRNN models by cross-validation. In the testing process, only the last set of the sensor signals of each engine in the testing set is selected for prediction.

Given that the engine works steadily at the early age and deteriorates linearly until it fails. Herein, we adopt the usual label processing method, that is, piecewise linear label, which assigns a constant value to the target label of the early monitoring signal (for the C-MAPSS dataset, take 125 as the constant RUL label) [41]–[43].

Two commonly used performance metrics, Score and root MSE (RMSE) [44], are used to evaluate the performance of the proposed method. Both of the performance metrics indicate the deviation degree between the predicted values and the actual values. Lower score and RMSE values mean that the prediction results are closer to the actual values. It also indicates that the prediction accuracy of the model is higher. The formulations of the two metrics are given as

$$\text{Score} = \sum_{i=1}^{N} \begin{cases} \exp\left(-\frac{d_i}{13}\right) - 1, & \text{if } d_i < 0 \\ \exp\left(\frac{d_i}{10}\right) - 1, & \text{if } d_i \geq 0 \end{cases} \tag{20}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} d_i^2} \tag{21}$$

where d_i represents the deviation between the predicted RUL and real RUL of the ith testing engine.

In addition, all the works were accomplished with Anaconda and python 3.6 and executed on a computer with Intel Core i5-4460 (3.20 GHz) CPU, 16-GB memory, and Microsoft Windows 10 Enterprise operating system.

B. Parameters Optimization

Multiple hyperparameters of the proposed method need be adjusted, that is, the hidden cell layers and the number of hidden neurons in the deep learning layer, the max depth of RDT, and the number of RDT models for iterative training in the EL layer.

1) Parameter Optimization of Deep Learning Layer: The performance of the DBRNNs is affected by many factors, such as model structure and training methods. Hence, the grid search algorithm is utilized to explore the optimized parameters in the DBRNN layer.

Taking the optimization of the number of the neurons in the hidden cell layer as an example, comparative experiments are conducted by using three DBRNNs, respectively. For comparison, the penalty factors of the loss function SLF are set to $\alpha_1 = 0.08$ and $\alpha_2 = 0.1$. Fig. 7 shows the average RMSE and training time over ten runs obtained by the DBRNNs on FD001, as the number of hidden neurons increases from 50 to 300. It is found in Fig. 7 that RMSE has a significant negative correlation with the average training time. Lower RMSE usually means higher training accuracy, and higher training accuracy often requires more resource costs. For TRNN and GRU, it is seen in Fig. 7 that as the neurons increase, their RMSE increases and the training time decreases. It means that the overfitting might occur in the training process, especially in TRNN, and this leads to the decreased training time and the lower accuracy of the network models.

Table III shows the relationship between the number of average training epochs of the three DBRNNs and the hidden neurons. The results showed that the epochs decrease as the neurons increase, which means that an excessive number of neurons may cause the model more likely to fall into a local minimum. Besides, compared with the Bi-LSTM network and

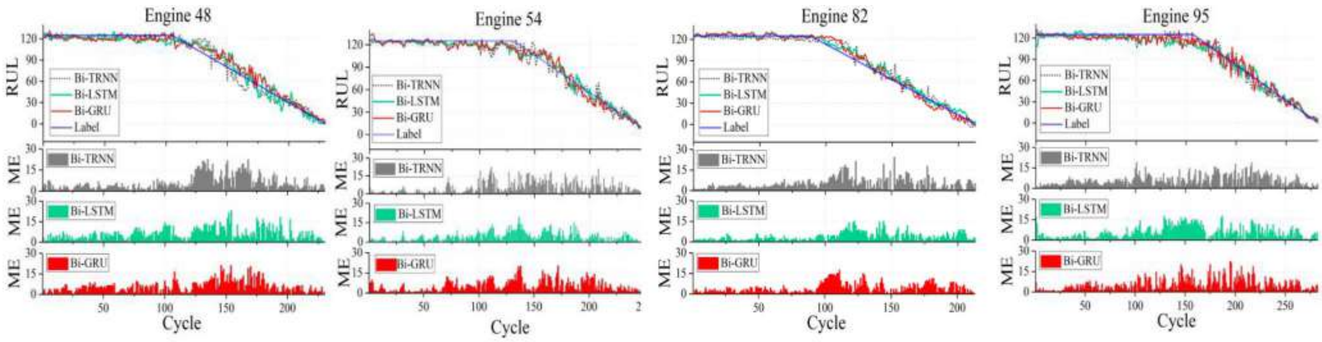

Fig. 8. Comparison of verification results of the three DBRNNs.

TABLE III
EPOCHS OF EARLY STOPPING FOR THREE DBRNNS

Number of neurons	Bi-TRNN	Bi-GRU	Bi-LSTM
50	386	292	346
100	219	275	289
150	89	272	256
200	44	251	174
250	46	257	220
300	44	206	231

TABLE IV
HYPERPARAMETERS OF TRAINING MODEL

Hyper-parameters	Bi-TRNN	Bi-GRU	Bi-LSTM
Neurons	150	250	300
Layers	3	3	3
Dropout	0.5	0.6	0.6
Batch size	8	8	8
Epoch	1000	1000	1000
Early-stop	15	15	15
Initial learning rate	0.001	0.001	0.001

Bi-GRU network, the training time of the Bi-TRNN is one order of magnitude less. This is because the simpler neuron structure of the TRNN will cause the lower computational costs of calculation. Finally, the number of neurons of the Bi-TRNN, Bi-GRU, and Bi-LSTM is set to 150, 250, and 300, respectively.

The results of the hyperparameter optimization are shown in Table IV, and each result is the average of ten repeated experiments. In Table IV, layers denote the number of hidden cell layers in the DBRNN models. Dropout presents the probability of dropping out units in the training process. The batch size is the number of samples selected for training, which has an effect on the training speed of the model. Epoch is the maximum number of training, and early stop denotes the number of iterative epochs in which the loss deviation has not been reduced. Initial LR controls the initial rate of learning progress since the Adam optimizer is adopted to train the DBRNN models.

It is worth noting that the BRNN model with more hidden layers might have a stronger information representation ability theoretically. On the other side, more layers in the BRNN model tend to cause the gradient vanishing in information transmission between different layers and a low convergence efficiency in the model training process. After many experiments, the hidden layer number of the BRNN is determined as 3.

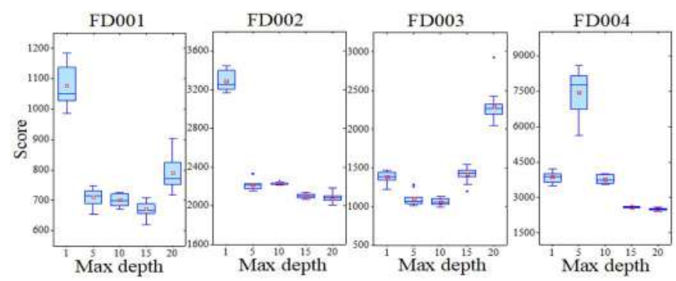

Fig. 9. Results of the RDT with different max depth.

Once the network training is completed, the performance of the model is tested by using the validation set. Fig. 8 shows the prediction results of four validation engines. It is found in Fig. 8 that all the three kinds of DBRNNs can fit the engine's RUL well. After hyperparameter optimization, the predicted mean error (ME) of RUL is within 30. The model also shows higher prediction accuracy for data points in the health state and near failure state.

2) Parameter Optimization of Ensemble Learning Layer: The proposed method uses multiple RDT models to ensemble the DBRNNs. The max depth and iteration number of the RDT model have a very important impact on the performance of the proposed method.

To determine the optimal max depth, the performance of the RDT models with different max depth parameters is compared by using the four subdatasets. Fig. 9 shows the distribution of the score over 15 runs, as the number of max depth increases from 50 to 300 at intervals of 5. The lower the score indicates the less deviation, which means the more accurate the predicted RUL value is. It is found from Fig. 9 that as for datasets FD001 and FD002, the RDT model achieves higher prediction accuracy when the max depth is between 5 and 15. But this value is raised to 20 when it comes to FD002 and FD004. This is because the operation modes of the engines contained in the two datasets are more complex and the RUL prediction domain is larger. So more spatial partitions are needed to improve accuracy.

Once the max depth of the RDT model is set, it is necessary to find the iteration number of the models. Fig. 10 shows the

TABLE V
PERFORMANCE COMPARISONS OF DIFFERENT MODELS ON THE DATASET FD001

Methods	SCORE	RMSE	Model training times (s)	Online average calculation times (s)
Bi-TRNN	692.78	19.09	1068	0.21
Bi-GRU	580.04	18.77	23387	0.36
Bi-LSTM	513.11	18.22	30261	0.28
DBRNNE with MSELF	498.23	18.09	153497	0.71
DBRNNE with SLF	459.89	17.97	164737	0.73

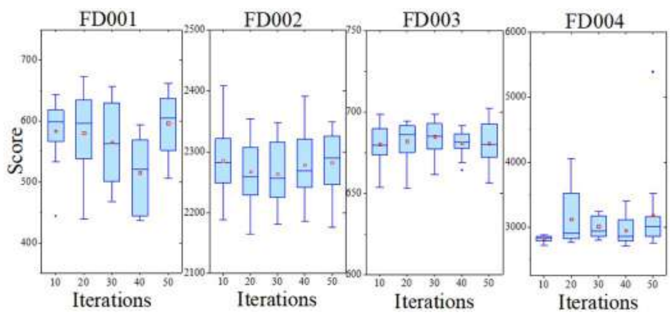

Fig. 10. Results of the RDT with different iteration number.

impact of the iterative number on the prediction accuracy of the four subdatasets. The parameters are changed from 10 to 50 at intervals of 10, and 15 runs are carried out for each group of parameters. The results show that for datasets FD001 and FD003, the predictions have better performance when the number of iterations is about 40. As for FD002, 30 iterations are regarded as the best, and ten iterations have better performance on FD004.

C. Results and Comparison

After parameter optimization, the structure of the models is determined. The steps in Section IV are performed in a sequence to train the constructed models. Then, the sensor signals of the testing engines are fed into the trained DBRNN ensemble model to realize the RUL prediction.

The predicted RUL of the engines in the four testing datasets is shown in Fig. 11, which are sorted by the real RUL from small to large. In this article, an RUL threshold is set, which has been widely used in literature [19], [41]–[43]. The results show that the predicted RUL values are close to the actual RUL values, and the prediction accuracy is even higher when the prediction point is closer to the end of life, which illustrates the remarkable performance of the proposed DBRNN ensemble model in RUL prediction. Compared with FD002 and FD004, the prediction deviation of FD001 and FD003 seems to be smaller, which indicates that the proposed method has higher prediction accuracy under a single operation mode. In addition, due to the introduction of the asymmetric loss function, the predicted RUL value tends to be higher than the actual value, and this is very promising for industrial applications.

Table V compares the prediction results of five models based on two evaluation metrics and time consumption. Among them, DBRNNE with MSELF represents that the model is trained with the traditional MSE loss function, and DBRNNE with SLF represents that the model is trained with the proposed SLF loss function. The experimental results show that the proposed DBRNNE model is superior to all other models in terms of score and RMSE. Since the network structure of Bi-TRNN is the simplest, the prediction results of Bi-TRNN are relatively worse compared with other advanced RNN structures. In addition, compared with DBRNNE with MSE, DBRNNE with SLF has about 8% improvement in the score metric, which means that the proposed SLF can improve the prediction accuracy of the DBRNNE model. In terms of time consumption analysis, since DBRNNE integrates multiple base learners, the model training time will increase significantly. It should be noted that the DBRNNE trained with SLF takes longer training time than that trained with MSELF. This is because the stage of the partial derivative of the SLF is more computationally expensive than MSELF. Considering that the training stage of the prediction model is generally performed offline, more time spent on training is acceptable. However, the online average calculation time of all models is less than 1 s on a normal personal computer, which proves that the proposed DBRNNE model can be applied to industrial applications.

The C-MAPSS dataset used in this article is very popular in the field of prognostic and already has many the latest research results. Many prognostic methods are adopted to compare with the proposed methods, including Earlier CNN [45], multiobjective deep belief networks ensemble (MODBNE) [10], multiobjective MLP ensemble (MOMLPE) [10], multiobjective SVM ensemble (MOSVME) [10], DCNN [19], bidirectional handshaking LSTM (BHLSTM) [40], Markov [46], deep LSTM (DLSTM) [28], Bayes [47], ensemble LSTM (ELSTM) [48], Bi-TRNN, Bi-LSTM, and Bi-GRU.

Table VI shows the comparison results with other published literature on the C-MAPSS dataset, where N/A means the information is unavailable. It is found in Table VI that the proposed method has the lowest score and RMSE on FD002 and FD004, and also has competitive and promising results on FD001 and FD003. The detailed discussions about the result comparison are summarized as follows.

1) Many machine learning algorithms (such as Markov and Bayes) have shown their advantages in this prediction problem. Compared with these traditional machine learning methods, the proposed method shows incomparable advantages.
2) Many methods have very good prognostic results on FD001 and FD003, however, poor performance for FD002 and FD004. This is because FD001 and FD003 have only one operating condition while FD002

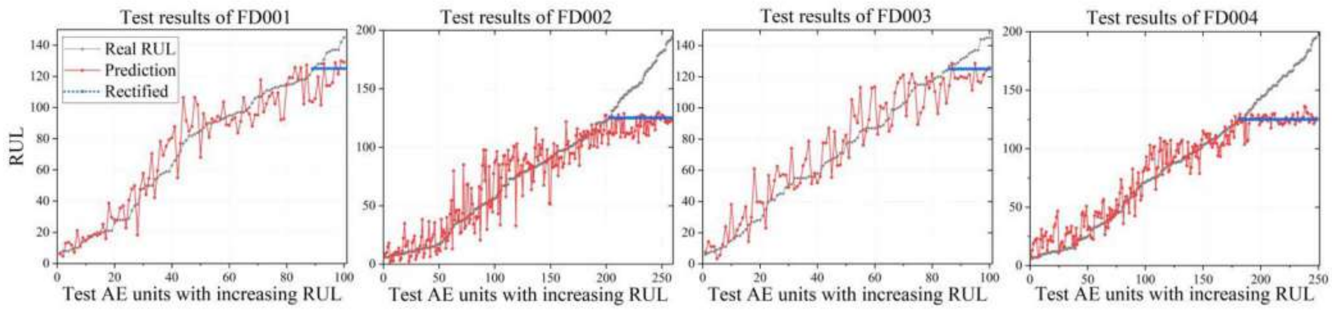

Fig. 11. Sorted RUL prediction of the engines in four testing datasets.

TABLE VI
PERFORMANCE COMPARISONS OF THE PROPOSED METHOD AND THE LATEST RELATED PAPERS ON THE C-MAPSS DATASET

Methods	Year	FD001		FD002		FD003		FD004	
		SCORE	RMSE	SCORE	RMSE	SCORE	RMSE	SCORE	RMSE
Earlier CNN [45]	2016	1286	18.45	13570	30.29	1596	19.82	7890	29.17
MODBNE [10]	2017	334.23	15.04	5585.34	25.02	421.91	12.51	6557.62	28.66
MOMLPE [10]	2017	560.59	16.78	14026.72	28.78	479.85	18.47	10444.35	30.96
MOSVME [10]	2017	7703.33	40.72	316483.31	52.99	22541.58	46.32	141122.19	59.96
DCNN [19]	2018	**273.7**	**12.61**	10412	22.36	**284.1**	**12.64**	12466	23.31
BHLSTM [40]	2019	376.64	N/A	N/A	N/A	1422	N/A	N/A	N/A
Markov [46]	2019	N/A	N/A	N/A	N/A	N/A	N/A	3572	26.85
DLSTM [28]	2020	655	18.33	N/A	N/A	828	19.78	N/A	N/A
Bayes [47]	2020	N/A	N/A	N/A	25.9	N/A	N/A	N/A	N/A
ELSTM [48]	2021	571	18.22	N/A	N/A	839	23.21	N/A	N/A
Bi-TRNN	2021	692.78	19.09	2936.91	21.56	823.49	20.37	3636.00	25.92
Bi-LSTM	2021	580.04	18.77	2435.99	20.93	769.36	19.48	3164.66	20.50
Bi-GRU	2021	513.11	18.22	2322.89	20.54	778.72	19.94	3282.47	23.97
Proposed method	2021	459.89	17.97	**2064.39**	**19.81**	658.12	19.18	**2869.67**	**20.40**

and FD004 have six. More operating conditions usually mean more complex data forms, which puts forward higher requirements for feature extraction and analysis ability of the model. The best performance on FD002 and FD004 among all the state of the arts demonstrates the superiority of the proposed DBRNN ensemble prognostic model.

3) Since FD001 and FD003 are relatively simple, many methods, such as DCNN, MODBNE, and MOMLPE, focus on optimizing the results on these two subdatasets and ignore the further optimize for the others, resulting in excellent results on FD001 and FD003, but relatively poor results on FD002 and FD004. Different from other deep learning methods, the proposed method considers the prediction requirements of four subdatasets at the same time, where network structures are shared on all the subdatasets. This makes the proposed method has the best results on FD002 and FD004 and competitive results on FD001 and FD003 compared with earlier CNN, DCNN, BHLSTM, DLSTM, and three DBRNN models.
4) The prediction results of many other EL methods, such as MODBNE, MOMLPE, MOSVME, and ELSTM, are also recorded in Table V. It is seen that the proposed DBRNN ensemble method achieves promising prediction results compared with these EL methods, which proves the robustness of the proposed method in different working conditions.

VI. CONCLUSION

In this article, a new DBRNN ensemble method is proposed for accurate and robust RUL prediction of the AE. In this method, three kinds of DBRNN models with different neuron structures are set up to extract hidden features from sensory data in both forward and backward directions simultaneously. A new customized loss function is designed to assess the performance of these DBRNN models. The cross-validation and early stopping techniques are introduced to prevent the models from overfitting. Meanwhile, an EL method for RUL estimation is established by using multiple RDT models. The proposed method is evaluated on the C-MAPSS dataset. The experimental results show that the proposed method has a better performance compared with other existing methods.

In the future, we will explore distributed adaptive methods by considering the limited amount of historical monitoring data among the dataset in different operating conditions so that the proposed method might be adaptively adjusted to achieve the diversification and generalization of the application scenarios.

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Appendix C

Tools Used

C.1 Software Tools:

- Python 3.9+
- Jupyter Notebook
- VS Code
- Github
- Overleaf

C.2 Hardware Tools:

- RAM: 4GB
- HDD/SSD: 256GB
- Graphics Card
- Intel Core i7 Processor

Appendix D

Papers Published/Certificates

D.1 Review Paper

- Title: A Comprehensive Survey of Predictive Maintenance Techniques for Aircraft Engines Utilizing the C-MAPSS Dataset.
- Authors: Muskan Pathan , Sneha Bhaskar , Vijayraje Jadhav , Vedant Kulkarni , Komal Gaikwad
- Published in: International Journal of Scientific Research in Engineering and Management (IJSREM) on Volume 08.
- Publication Year: 2024

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

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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 Restricted Boltzmann Machines (RBMs), Long Short-Term Mem ory (LSTM) networks, Convolutional Neural Networks (CNNs), and Deep Bidirectional Recurrent Neural Networks (DBRNNs) is one prominent method. Features are chosen and models are optimized using a variety of methods, including Genetic Algorithms, Recursive Feature Elimination, Lasso, and Feature Importances. In prognostic modeling, the research emphasize the need of interpretability, model adaptability, and 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 comprehensive and realistic assessments of prognostic models under real-world flight conditions, providing useful tools for benchmarking and improving machine learning algorithms in predictive maintenance. All things considered, these research projects highlight current developments and the possibility of combining cutting edge technology to improve system reliability, improve predictive maintenance techniques, and guarantee safer airline operations.

Key Words**:** Aircraft engine, Prognostics, Predictive main tenance, Machine learning, Deep learning, Remaining Useful Life (RUL), Aviation safety, Feature engineering, Ensemble learning, Uncertainty quantification, Explainable AI, Bayesian Deep Neural Networks (DNNs), Gaussian Processes (GPs), N CMAPSS dataset, Real flight conditions, Industrial assets, System reliability, Benchmarking.

1. INTRODUCTION

Recent developments in deep learning and machine learn ing techniques have caused a paradigm change in the avia tion sector toward proactive maintenance measures. Modern research approaches to improve aviation engine predictive maintenance are explored in this review paper. The meth ods covered by these approaches include deep learning ar chitectures such as LSTM networks and Convolution-Based LSTM (CLSTM) networks, as well as feature engineering, ensemble learning, and genetic algorithms. New methods for forecasting the remaining usable life (RUL) of aviation engines, like the ensemble of Deep Bidirectional Recurrent Neural Networks (DBRNNs) and aggregated feature impor tance with cross-validation (AFICv), perform competitively. Furthermore, research employing uncertainty-aware prediction techniques—like Bayesian Deep Neural Networks (DNNs) and Deep Gaussian Processes (GPs)—offers insights into uncer tainty assessment that is essential for maintenance decision making. The importance of high-quality datasets, such as the N-CMAPSS dataset, which is obtained from actual flight conditions, is also emphasized, highlighting the role that these datasets play in the development and validation of sophis ticated prognostic models. This review paper highlights the transformative potential of machine learning and deep learn ing in enhancing aviation safety, optimizing aircraft engine performance, and improving operational efficiency through accurate RUL predictions and proactive maintenance strategies by synthesizing insights from diverse research methodologies.

2. Literature Survey

The research paper introduces a comprehensive methodology for estimating the remaining useful life (RUL) of aviation engines. The methodology includes a multi-stage structured data processing pipeline, including techniques like data preprocessing, rolling time series window aggregation, principal component analysis, Genetic Algorithm, Recursive Feature Elimination, Lasso, and Feature Importances from a Random Forest model. The efficacy of the chosen features is assessed using four machine learning regression models: Multi-Layer Perceptron (MLPRegressor), Random Forest (RandomForestRegressor), Extreme Gradient Boosting (XGBRegressor), and Natural Gradient Boosting (NGBRegressor). The study shows competitive performance across the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) sub datasets. The research also presents a novel technique called aggregated feature importances with cross-validation (AFICv) to rank features according to their mean importance and improve the generalizability of machine learning models. The research highlights the potential of this approach in enhancing maintenance procedures and increasing aircraft engine performance through precise RUL predictions, despite constraints like data availability and processing costs[1].

The research paper presents ProgNet, a novel machine learning solution for predicting aircraft engine damage under real flight conditions. The study uses the N-CMAPSS dataset, which provides authentic sensor data from actual flight scenarios. ProgNet is designed to handle the complexities of aircraft engine data, including non-linearity, non stationarity, and noisy sensor readings. It demonstrates superior performance in reducing root-mean-squared error compared to traditional deep learning methods. This development sets a new standard in prognostic modeling for safety-critical systems, offering a robust and adaptable solution to the challenges faced in machine learning prognosis within the aviation industry. The findings provide valuable insights for future research and contribute to the advancement of predictive maintenance strategies and decision-making processes in the aviation sector[2].

The study presents a novel method for utilizing the Deep Bidirectional Recurrent Neural Networks (DBRNNs) ensemble to predict the remaining useful life (RUL) of aircraft engines. To extract hidden features from sensory data, the method entails creating numerous DBRNNs with varied neuron architectures. A set of RUL values is obtained by designing a customized loss function to assess the DBRNNs' performance. Following that, these values are reencapsulated into a projected RUL domain, where multiple regression decision tree (RDT) models are used to iteratively update the element weights. High precision f inal RUL prognostics are obtained by merging the projected results from various DBRNNs. NASA C-MAPSS datasets are used to validate the suggested approach, which shows improved performance over current approaches. The study emphasizes how crucial PHM is for raising aviation engine reliability and lowering maintenance costs. By skillfully fusing deep learning with ensemble learning methodologies, the DBRNN ensemble approach provides a reliable and accurate solution for RUL prediction. The study advances the f ield by demonstrating the effectiveness of integrating deep learning and ensemble approaches for PHM and improving RUL prediction capabilities for intricate systems like aircraft engines[3].

The research paper by Owais Asif et al. presents a deep learning model employing LSTM networks for forecasting the remaining useful life (RUL) of aircraft turbofan engines using the C-MAPSS dataset. The paper introduces a unique piecewise linear degradation model to determine the start of engine deterioration and assign RUL labels, validated with the C-MAPSS dataset. Pre-processing techniques such as correlation analysis and filtering enhance data quality. The LSTM network, trained on pre-processed sensor data and updated RUL labels, achieves improved prediction accuracy across all C-MAPSS sub-datasets. The study showcases the model's effectiveness for turbofan engine predictive maintenance. Future research directions include enhancing model generalization, evaluating performance across diverse datasets, and exploring advanced data preprocessing methods to further enhance deep learning algorithm capabilities. This research significantly contributes to predictive maintenance methods in industrial automation, offering valuable insights on optimizing RUL prediction within the Industry 4.0 framework[4].

The research study explores the application of LSTM neural networks to predict aircraft engine failure for ensuring aviation safety. The study utilizes AI and Deep Learning with LSTM networks to forecast the remaining usable life (RUL) of engines using historical flight data and 21 sensor readings per aircraft. The model architecture, comprising two LSTM layers and a Dense layer, achieved an impressive 90.8% recall rate during evaluation. A comparative study shows that the LSTM-based strategy outperforms conventional statistical techniques, providing more accurate RUL estimations for efficient maintenance scheduling. Future prospects involve refining the model to handle larger datasets effectively and enhancing prediction accuracy by integrating new data sources. These developments aim to support maintenance plans, optimize operational efficiency, and adhere to aviation safety regulations. The study highlights the significance of leveraging advanced technology like LSTM neural networks in predictive maintenance, offering an early strategy for reducing engine failures in the aviation sector. The research contributes to advancing predictive maintenance techniques, thereby enhancing the dependability and safety of aircraft operations through iterative improvements to the model's capabilities[5].

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The research study proposes a novel method for evaluating the remaining usable life (RUL) of aircraft engines by combining Light Gradient Boosting Machine (LightGBM) and deep convolutional neural networks (DCNN). This approach utilizes raw sensor data instead of traditional signal processing methods, leading to improved precision and effectiveness in RUL prediction. The DCNN employs a leaf-wise technique to enhance prognosis accuracy, while LightGBM leverages time series sensor data to extract complex characteristics. Experiments conducted using NASA's C-MAPSS dataset demonstrate the effectiveness of the proposed model in estimating the RUL of aircraft engines. By leveraging the boosting capabilities of LightGBM and the deep learning capabilities of DCNN without requiring human feature engineering, the model achieves excellent accuracy in RUL estimation. The study highlights the need for further model structure and hyperparameter tuning to reduce training times and computational burden. Future research will focus on applying the proposed technique to RUL prediction in diverse operational scenarios to address challenges posed by complex engine operations. This work opens up opportunities to enhance RUL estimates in aerospace applications by leveraging cutting-edge deep learning approaches[6].

The study introduces a unique technique for improving the precision of aeroengine remaining useful life (RUL) prediction by quantifying uncertainties, termed prediction interval estimation. This methodology integrates deep learning algorithms, mathematical-statistical analysis, and data clustering in both offline and online phases. During the offline phase, aeroengine health states are categorized using an enhanced fuzzy c-means method, and prediction intervals are computed using empirical error distributions. To estimate the boundaries of RUL prediction intervals, an online phase utilizes a bidirectional long short-term memory (Bi-LSTM) network. The method's performance is evaluated using metrics like the Coverage Width-Based Criterion, PI Normalized Averaged Width, and PI Coverage Probability. The analysis of results using NASA's aeroengine degradation dataset demonstrates the method's effectiveness in providing reliable RUL interval estimations for maintenance-related decision-making. Future research aims to assess the method's applicability in scenarios with variable operating conditions and limited data availability, as well as to determine optimal maintenance practices based on generated RUL prediction intervals[7].

The research paper introduces a novel deep learning model called Convolution-Based Long Short-Term Memory (CLSTM) network for accurate prediction of Remaining Useful Life (RUL) in rotating machinery. By integrating time-frequency and temporal information from vibration signals, the CLSTM network is designed to extract temporal time-frequency characteristics using convolutions to model input-to-state and state-to-state transitions. The methodology's effectiveness is confirmed through run-to-failure bearing tests, showing superior performance compared to other deep learning techniques. The study suggests that optimizing the CLSTM architecture could lead to shorter training times and improved practical applicability in complex systems with multiple components. The CLSTM network represents a significant advancement in RUL forecasting, offering enhanced precision and computational efficiency, which addresses the need in Prognostics and Health Management (PHM) for reducing maintenance costs and increasing system reliability. Real-world datasets are used to thoroughly evaluate the model's effectiveness, considering criteria such as accuracy and efficiency in RUL prediction. The study presents encouraging results from extensive testing and analysis, demonstrating the superior performance of the deep-convolution-based LSTM network over traditional approaches. Overall, the study contributes a novel framework that leverages deep learning for proactive maintenance decision-making, making a substantial impact in the field of industrial informatics[8].

The research introduces a method to predict the Remaining Useful Life (RUL) of industrial assets using a combination of neural networks and Gaussian Processes (GPs) to capture uncertainty in forecasts. The study explores various methodologies, including Deep Learning and Bayesian Deep Neural Networks (DNNs), aiming to provide predictive analytics and insightful uncertainty evaluations. Evaluation metrics such as Root-Mean-Square Error (RMSE), Negative Log-Likelihood (NLL), and Differential Softplus Probabilistic Predictions (DSPP) are used to assess performance. The study finds that DSPP produces the highest NLL score, while Minimum Covariance Determinant (MCD) performs better in terms of RMSE. Both DSPP and MCD models provide confidence boundaries that demonstrate decreasing uncertainty as the system nears its end of life. These models are effective with large training datasets and are scalable. The paper suggests areas for further research to improve the capture of temporal correlation in time-series data. It also compares these methods to modern Bayesian DNNs to enhance performance by exploring advanced Bayesian strategies for uncertainty estimates and better integration of temporal information. In conclusion, the study underscores the importance of uncertainty-aware prognosis in industrial asset management and lays the groundwork for future developments in this field[9].

The N-CMAPSS dataset is introduced in the paper, which improves the fidelity of prognostics and diagnostics for aviation engines. The dataset includes fault class labels, health condition labels, and run-to-failure trajectories for a fleet of turbofan engines based on enhanced degradation modeling and real flight conditions. The degradation model replicates beginning, normal, and pathological degradation, with fault onset connected to the operation history. Control tests and quality assurance procedures ensure the dataset's integrity, which has been used in earlier research for data driven prognostics and model-based diagnostics. The dataset serves as a standard for comparing algorithms and aids in the development of deep learning algorithms for predictive maintenance. It can also be utilized to create new machine learning algorithms informed by physics. The study suggests future enhancements to the turbofan engine degradation process and extensions to accommodate more defect types and onboard sensors. Overall, the N-CMAPSS dataset provides improved fidelity for aircraft engine prognostics and diagnostics, making it a valuable resource for the machine learning community[10].

In the publication, a deep-stacked convolutional Bi-LSTM model is introduced to predict the remaining useful life (RUL) of a turbofan engine. The model integrates Long Short-Term Memory (LSTM), bidirectional LSTM, and one-dimensional convolutional neural networks (CNNs). To prevent overfitting, dimensionality reduction strategies such as regularization and correlation analysis are employed. Furthermore, explainable AI techniques, specifically the Shapley additive explanation (SHAP) method, are used to identify sensors with significant impacts on prediction outcomes. When evaluated using NASA's C-MAPSS dataset, the model outperforms other studies in terms of accuracy. By eliminating unnecessary input sensors through correlation analysis, accuracy is further improved. The SHAP technique provides clear insights into the important elements influencing the RUL of the turbofan engine. The study suggests further exploration of deep learning models for complex system health monitoring and prognostics. It also underscores the importance of explainable AI methods in comprehending and analyzing outputs from deep learning models[11].

The research paper investigates the use of deep learning techniques for turbofan engine remaining useful life (RUL) prediction. The methodology uses Restricted Boltzmann Machines (RBM) to extract features from the C-MAPSS dataset in an unsupervised pre-training phase that is semi supervised. To improve the accuracy of RUL prediction, deep architecture hyperparameters are optimized using a Genetic Algorithm (GA). With less labeled training data, the evaluation shows how successful the semi-supervised method is in producing promising RUL predictions. The investigation demonstrates how unsupervised pre-training can be applied in practical applications related to health management and prognostics. In order to increase model performance, future study will explore sophisticated unsupervised DL techniques such as Variational Autoencoders (VAE) and optimize training times as well as scalability. This work provides important new understandings for improving system safety and reliability engineering in the prediction of turbofan engine degradation[12].

The research employs the C-MAPSS simulator to model the spread of damage in gas turbine aircraft engines. In addition to discussing damage propagation modeling, it analyzes health parameter modeling, introduces the simulation model, and tackles the prognostics problem. The PHM competition used the generated data to evaluate performance. The study examined how damage spread in engine modules was modeled using the C-MAPSS simulator, offering insights into the creation of prognostic algorithms and performance assessment for PHM applications. The significance of precise modeling for successful prognostics solutions is emphasized throughout the research. Prospective avenues for research encompass enhancing prognostic algorithms, optimizing damage propagation models, and investigating supplementary data situations to augment predictive maintenance tactics for aviation engine health monitoring. The paper discusses performance evaluation and key metrics for PHM applications, and it offers insights into creating and testing prognostics algorithms using the C-MAPSS simulator. The importance of accurate modeling for successful prognostics solutions is emphasized throughout the article. In order to improve predictive maintenance techniques for aviation engine health monitoring, future research opportunities include improving prognostics algorithms, improving damage propagation models, and investigating a variety of data situations and settings[13].

3. CONCLUSION

Innovations in aircraft engine prognostics and predictive maintenance are demonstrated in the evaluated publications. Remaining Useful Life (RUL) can be predicted more accu rately by deep learning models such as CNNs, RBMs, and LSTM networks than by more conventional techniques, and these models deal well with complex data. By ranking fea tures according to relevance and integrating models, ensemble techniques like DBRNNs ensemble and LightGBM with DC NNs improve prediction accuracy. Critical confidence bounds are provided for maintenance decision-making by integrating uncertainty-aware prognosis with Deep GPs. The models' practical applicability is ensured by validation using real-world datasets such as C-MAPSS and N-CMAPSS. Future topics for study include combining operational data sources, fine tuning damage propagation models for better prognostics, opti mizing model hyperparameters, and investigating cutting-edge deep learning approaches. In summary, these investigations considerably progress the field of aircraft engine prognostics and augment aviation safety, dependability, and operational effectiveness within the aerospace sector.

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