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Turbofan Engine Remaining Useful Life Prediction Using 1-Dimentional Convolutional Neural Network

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ABSTRACT

Turbofan engines have been the dominant type of engine in aircraft for the last forty years. Ensuring the quality of these engines is crucial for flight safety, particularly for long-distance flights. However, their performance degrades over time, impacting flight safety. To address this issue, it is essential to predict potential engine failures by estimating the Remaining Useful Life (RUL) of the engines Deep learning, especially Convolutional Neural Networks (CNNs), has demonstrated exceptional proficiency in handling intricate, non-linear data, leading to improved RUL predictionsdue to their ability to process complex and non-linear data. In this project, a 1-D CNN is used to predict RUL using the NASA C-MAPSS FD001 dataset, which consists of 3 settings and 21 sensors, though sensors with stagnant readings are excluded. The dataset is normalized using min-max and z-score methods, and then segmented into sequences for input into the 1-D CNN model. Various training scenarios were evaluated, with the best RMSE of 3.26 achieved using 10 epochs, a learning rate of 0.0001, and z-score normalization. The results indicate that feature selection can produce a lower RMSE compared to scenarios without feature selection.

Keywords: CNN, Prediction, Remaining Useful Life, RUL, Turbofan Engine

1. INTRODUCTION

Turbofan engines have been the predominant choice for aircraft designed over the past 40 years[1]. Ensuring the optimal performance of turbofan engines is crucial for safe flights, especially for long-distance travel [2]. Over time, however, the quality of these engines deteriorates, leading to decreased performance and potential safety risks. Regular maintenance is necessary to enhance engine quality and restore performance, which involves predicting potential engine failures through Remaining Useful Life (RUL) estimation [3]. RUL is critical as it indicates the time left until the end of an engine's useful life, reflecting its health status[4].

Various methods, including machine learning and deep learning, have been employed to predict RUL. Deep learning, especially Convolutional Neural Networks (CNNs), has demonstrated exceptional proficiency in handling intricate, non-linear data, leading to improved RUL predictions [5]. Among these, 1-Dimentional CNNs have been effectively used for RUL prediction in turbofan engines [6]. Despite previous research, detailed aspects like sensor selection remain underexplored. Proper sensor selection can reduce prediction errors, as constant sensors may not provide

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useful degradation information [7]. Additionally, the "no free lunch" theorem suggests that no single algorithm is universally best for all problems, indicating room for optimizing the employed algorithms [8]. Hyper Parameter Optimization is one method to enhance algorithm performance [9].

In this study, we propose employing a 1-Dimensional CNN model adapted from the model in the study by [6], with the activation function modified from tanh to ReLU, and we perform both feature selection and non-feature selection scenarios.

This study aims to address the problem of predicting the RUL of turbofan engines using a 1-Dimentional CNN. The objectives are to predict RUL using a 1-Dimentional CNN model, compare the predicted RUL with the actual RUL, and compare RUL predictions with and without feature selection. By achieving these objectives, this research seeks to improve the accuracy of RUL predictions and optimize the CNN model used.

2. MATERIAL AND METHODS

In this research, the Knowledge Discovery in Database (KDD) method is used to uncover valuable information from data. This method employs data mining techniques to extract patterns from the data, which are then identified using algorithms. The flowchart of this research can be observed in Figure 1.

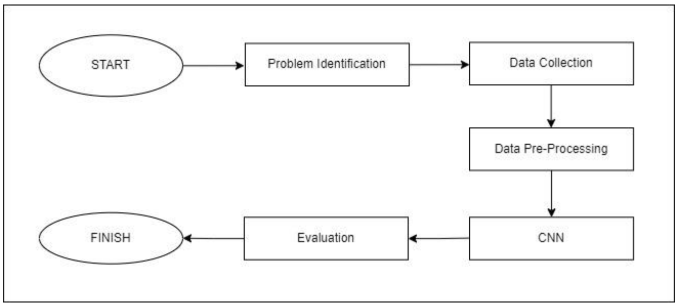

FIGURE 1. Research’s Flowchart

2.1 MATERIAL

The data used in this study is the NASA C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) [10]. This dataset contains detailed information about aircraft propulsion system simulations under various operational conditions. The engine that being used is shown in Figure 2.

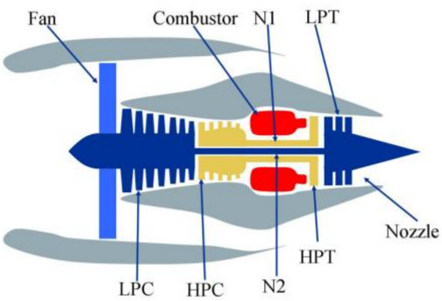

FIGURE 2. C-MAPPS Engine[10]

For this research, the C-MAPSS dataset used is FD001, which includes training data, testing data, and RUL from the training data. Each training and testing dataset contains data from 100 turbofan engines. Each of them has three operational settings and 21 sensors. From the three operational settings and 21 sensors in the dataset, signal visualization was conducted to identify those that vary across cycles. Among them, two operational settings (setting 1 and setting 2) and fifteen sensors (sensor 2, 3, 4, 6, 7, 8, 9, 11, 12, 13, 14, 15, 17, 20, and sensor 21) exhibit variations across cycles and are not stagnant. These will be used for future research purposes. All the operational settings and sensor from the C-MAPPS dataset that being used can be observed in Table 1.

TABLE 1.
NASA C-MAPPS Operational Settings and Sensors

Sensor No.	Name	Unit
1	Total temperature at fan inlet	Ro
2	Total temperature at LPC outlet	Ro
3	Total temperature at HPC outlet	Ro
4	Total temperature at LPT outlet	Ro
5	Pressure at fan inlet	Psia
6	Total pressure in bypass-duct	Psia
7	Total pressure HPC outlet	Psia
8	Physical fan speed	Rpm
9	Physical core speed	Rpm
10	Engine pressure ratio	-
11	Static pressure at HPC outlet	Psia
12	Ratio of fuel flow to “16”	pps/psi
13	Corrected fan speed	Rpm
14	Corrected core speed	Rpm
15	Bypass ratio	–
16	Burner fuel-air ratio	–
17	Bleed Bleed enthalpy	–
18	Demanded fan speed	Rpm
19	Demanded core fan speed	Rpm
20	HPT coolant bleed	lbm/s
21	LPT coolant bleed	lbm/s

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2.2 METHODS

2.2.1 CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Network (CNN) is an integral component of deep learning techniques. A standard CNN architecture usually comprises convolutional layers followed by pooling layers and culminates in fully connected layers. The convolutional layers are tasked with extracting features from the input, whereas the pooling layers reduce the data's dimensionality, thereby aiding in overfitting reduction. The fully connected layers are responsible for classifying the data based on the extracted features. The fundamental structure of a CNN is illustrated in Figure 3.

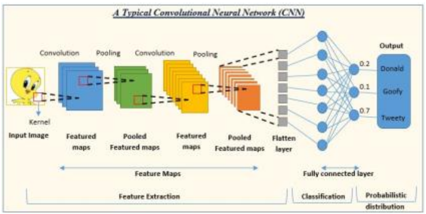

FIGURE 3. A Typical CNN

There has been extensive research on employing CNNs to predict the turbofan engine's RUL. One of the pioneering studies in this area was conducted by Babu et al., which used a 2-Dimentional CNN architecture for data extraction [11] Another notable study by Li et al., focused on predicting the turbofan engine's RUL using 1-Dimentional deep convolutional neural networks [6].

The 1-Dimentional CNN model employed in this research is adapted from the model in the study by [6], with the activation function modified from tanh to ReLU. The architecture of the model used in this research is illustrated in Figure 4.

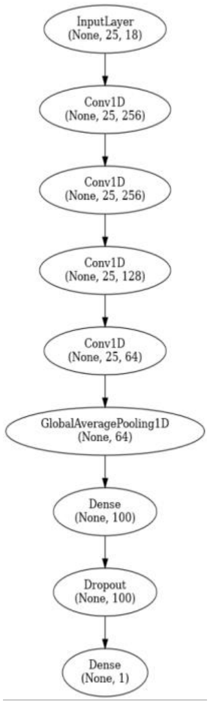

FIGURE 4. I-D CNN Architecture

2.2.2 ROOT MEAN SQUARED ERROR (RMSE)

RMSE (Root Mean Square Error) is a widely used metric for evaluating models in RUL prediction cases, as it compares the actual RUL with the RUL predicted by the model. RMSE can be defined using the following formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} h_i^2} \quad (1)$$

Where N is the number of engines, and h is the difference between the predicted RUL from the prediction and the actual RUL that given in the dataset.

2.2.3 REMAINING USEFUL LIFE (RUL)

Remaining Useful Life (RUL) is an essential concept in Prognostics and Health Management (PHM) for machines and systems. RUL denotes the remaining operational time of a machine or system before maintenance or component replacement is necessary. It can also refer to the duration left until the machine or system reaches the end of its useful life [4]. Additionally, RUL can be defined as the remaining period during which a component can continue to perform its functional tasks before failure occurs [12].

According to the research conducted by [13] in the initial exploration of RUL using the NASA C-MAPSS FD001 dataset, the following formula can be applied:

$$Last\ Cycle\ (Unit\ Number) - Current\ Cycle(i) = Remaining\ Useful\ Life\ (RUL) \quad (2)$$

2.2.4 DATA PRE-PROCESSING

The data collected during the data collection process then proceeds to the next stage, which is the data preprocessing stage. The data is preprocessed before being processed by the 1-D CNN model. Pre-processing method consist of feature selection, RUL labelling, and data normalization and sequencing.

3. RESULT AND DISCUSSION

The model that has been successfully created from the training process will enter the evaluation stage, using the test data as the test set. A random selection of 25 engines from the test data is made to serve as the evaluation test data. The metric used in the evaluation stage is RMSE.

Among the various training scenarios conducted, the smallest RMSE with feature selection was achieved which yielded an RMSE of 3.26. This scenario used a learning rate of 0.0001, the Adam optimizer, z-score normalization, and 10 epochs. The visualization of the train loss and validation loss for this scenario can be seen in Figure

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5, while the visualization of the predicted RUL values compared to the actual RUL values can be seen in Figure 6.

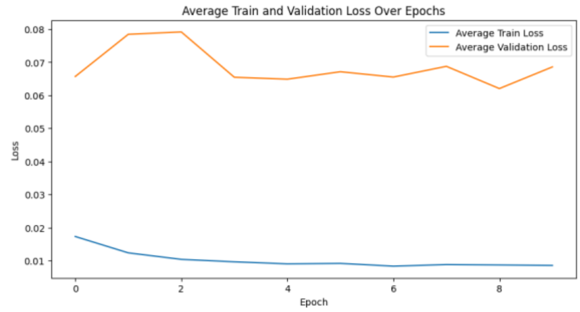

FIGURE 5. Train loss and val loss visualization

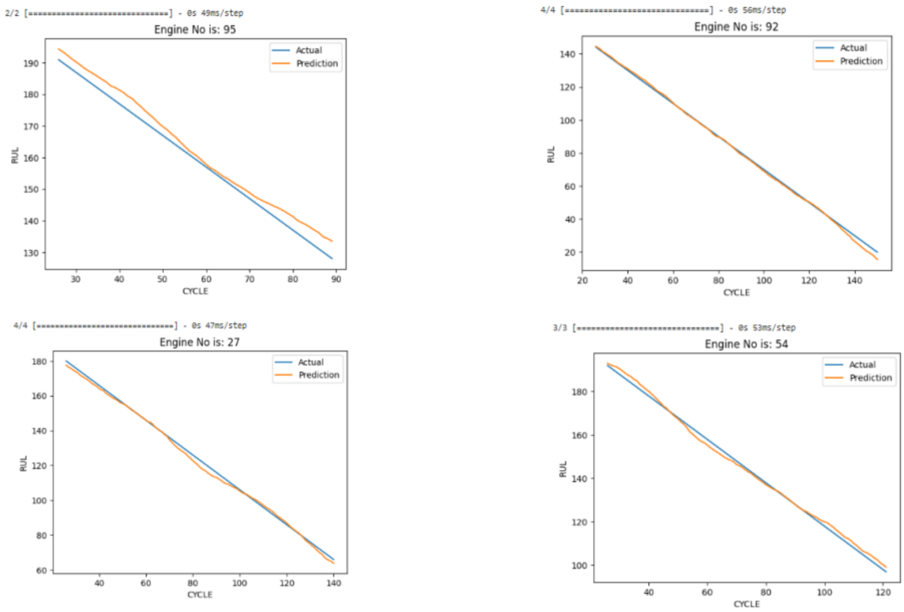

FIGURE 6. Visualization comparing the RUL per engine

In addition to using feature selection, scenarios were also conducted without feature selection. The smallest RMSE achieved without feature with an RMSE of 3.76. This scenario used a learning rate of 0.0001, the Adam optimizer, z-score normalization, and 20 epochs. The visualization of the train loss and validation loss for this scenario can be seen in Figure 7, while the visualization of the predicted RUL values compared to the actual RUL values can be seen in Figure 8.

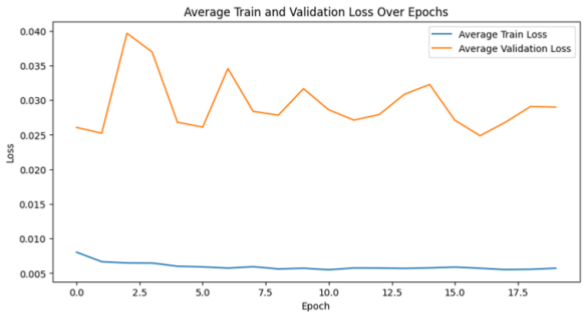

FIGURE 7. Train loss and val loss visualization without feature selection

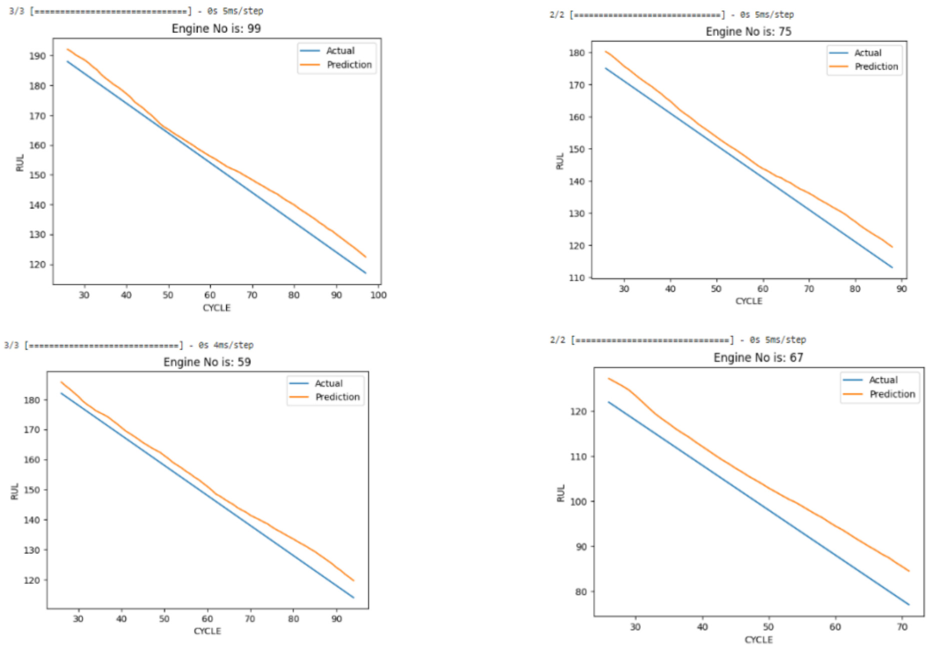

FIGURE 8. Visualization comparing the RUL per engine without feature selection

4. CONCLUSION

Based on the entire research process that has been conducted, the following conclusions can be drawn: the 1-Dimentional CNN method can be effectively used to predict Remaining Useful Life (RUL). Among the various testing scenarios performed, the best RMSE achieved was 3.26, using a learning rate of 0.0001, the Adam optimizer, z-score normalization, and 10 epochs. Additionally, the use of feature selection can result in a lower RMSE.

From these conclusions, the following recommendations can be made for future research: it is suggested to use other feature selection methods, such as correlation and others. Additionally, experimenting with different hyperparameter optimizers like SGD, RMSProp, and others could be beneficial. Exploring other data normalization methods, such as robust normalization, max abs normalization, and others, may also provide valuable insights. Furthermore, employing different activation functions, such as sigmoid, softmax, ELU, and others, could enhance model performance. Lastly, efforts should be made to develop a more optimal model to prevent overfitting.

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