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| **RESEARCH ARTICLE**

Remaining Useful Life Prediction of Turbofan Engines Using CNN-GRU: A Comparative Study on C-MAPSS Dataset

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| ABSTRACT
Accurate prediction of Remaining Useful Life (RUL) is crucial for effective predictive maintenance strategies in various industries. This study investigated the application of a combined Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) architecture for predicting the RUL of turbofan engines using the C-MAPSS dataset. The CNN-GRU model leverages the complementary strengths of both components, with the CNN extracting spatial features from sensor data and the GRU capturing temporal dependencies in sequential engine data. Preprocessing techniques such as windowing and data reshaping were employed to optimize the input for the deep learning model. Six CNN-GRU configurations were tested to identify the optimal architecture for each C-MAPSS subset (FD001, FD002, FD003, and FD004). The model performance was evaluated using Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) metrics. The results demonstrated that the CNN-GRU model effectively captured degradation patterns and accurately predicted RUL across all datasets, outperforming traditional machine learning methods, such as Multilayer Perceptron (MLP) and Support Vector Regression (SVR). The robustness and adaptability of the model to various operational scenarios highlight its potential for implementation in diverse industrial applications, enhancing predictive maintenance efforts, and improving overall operational efficiency. Future research should explore alternative configurations and consider increasing the number of training epochs to refine the prediction results further.

| KEYWORDS
Remaining Useful Life (RUL); CNN (Convolutional Neural Network); GRU (Gated Recurrent Unit); PdM (Predictive Maintenance)

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1. Introduction
In recent decades, as critical machinery has played an ever-important role in a range of industries from aviation through energy generation and the automotive industry, they have had to look more carefully than ever before to make faster yet better maintenance provisions for quick repairs (Kamat & Sugandhi, 2020; Velmurugan et al., 2022). Forecasting the Remaining Useful Life (RUL) is crucial in these plans (Lin et al., 2021). By predicting the RUL correctly, the likelihood of a sudden breakdown of machinery can be greatly reduced. These failure implications are massive, meaning it is more than a loss of money, including the threat on something far bigger than that- your career safety itself (Sekar et al., 2021). To address this issue, there seems to be a significant potential in the employment of machine-learning-based techniques as models capable of rendering RUL predictions more effective than the traditional model, that is, physical or statistical.
Lee et al (2018) suggest one machine learning approach to predict RUL through the amalgamation of Convolutional Neural Networks (CNNs), and Gated Recurrent Units (GRUs). The advantage of this model is twofold: it fully utilizes the ability of the CNN to extract useful space-dependent features in sensor data and also encompasses GRU temporal information that keeps up with relevant patterns present throughout time. In our previous study, we explored model architecture and software development (Azyus et al., 2023). Within this framework, a more comprehensive study on the theoretical basis of CNN-GRU is presented, and its

wider implication for RUL prediction beyond the PHM methodology has been established to offer further insights into how such a model could be applied in the real world.

The CNN-GRU approach offers several advantages over other methods such as Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP), particularly in terms of efficiency and simplicity (Yang et al., 2024). GRU, a streamlined version of LSTM, requires fewer parameters, which accelerates the training process while maintaining the capability to capture complex temporal relationships (Sekar et al., 2021). CNN excels in extracting spatial patterns from high-dimensional sensor data, making it highly suitable for applications involving continuously generated machine data. Our previous studies demonstrated that the CNN-GRU architecture performs competitively in Remaining Useful Life (RUL) prediction. However, this study seeks to delve deeper into the theoretical mechanisms behind these advantages and explore their practical applications across various industries (Azyus et al., 2023).

Previous research has extensively investigated the potential of combining Convolutional Neural Networks (CNN) with Gated Recurrent Units (GRU) to predict the Remaining Useful Life (RUL) across different industries. For instance, Baroud et al. (2024) explored how AI techniques, particularly CNNs and GRUs, can enhance predictive maintenance (PdM) strategies within mechatronic systems. Mazaev et al. (2021) employed Bayesian CNNs to predict the RUL of solenoid valves, highlighting the model's ability to deliver reliable uncertainty estimations that are critical for informed maintenance decisions. Hsu et al. (2022) introduced a Temporal Convolution-Based Long Short-Term Memory (TCLSTM) network combined with an attention mechanism, which significantly improved RUL predictions by efficiently extracting key features from sensor data.

Rivas et al. (2024) developed a PdM framework that integrated CNN-Autoencoder and Bayesian Neural Network models, optimizing maintenance strategies for pump bearings with great success. Likewise, Pebrianti et al. (2024) introduced a failure prediction model for the aerospace industry, utilizing CNNs to achieve superior accuracy compared with traditional Recurrent Neural Networks (RNN). Habib and Mohamed (2024) optimized hyperparameters for CNN and LSTM models, demonstrating enhanced RUL prediction performance across multiple datasets.

In the context of deep learning techniques, Narang et al. (2024) conducted a comparative analysis of machine learning techniques for predicting the Remaining Useful Life (RUL) of ball bearings, where a 1-D CNN achieved an impressive 99.17% accuracy, outperforming traditional methods. Zhou et al. (2021) proposed an Embedded Convolutional LSTM for RUL estimation, demonstrating its superiority over conventional techniques. Furthermore, Jafari and Byun (2023) introduced a hybrid CNN-GRU model for lithium-ion batteries, which effectively extracted relevant features from charging profiles to improve the prediction accuracy.

Shaw and Wu (2021) applied both machine learning and deep learning models to predict the RUL of aircraft turbofan engines, highlighting the crucial role of Recurrent Neural Networks (RNNs) in capturing temporal dependencies. De Barrena et al. (2023) ocused on bidirectional recurrent neural networks to forecast the RUL of cutting tools in manufacturing, underlining the importance of proper signal selection in RUL predictions. Mode et al. (2020) investigated the effects of false data injection attacks on deep learning-enabled predictive maintenance (PdM) systems, illustrating the vulnerabilities of IoT sensors and the resilience of GRU models in maintaining prediction accuracy despite data manipulation.

Despite these advances, much of the existing research is narrowly focused and is often limited to specific applications, without addressing the broader industrial context. Studies like those by Rebaiaia and Ait-Kadi (2022) in production systems and Pillai and Vadakkepat (2021) on two-stage deep learning for prognostics have highlighted the promise of CNN-GRU models, yet they lack a unified framework applicable across various industries.

The current literature reveals a gap in the comprehensive integration of CNN-GRU models into predictive maintenance systems for complex machinery in different sectors. This study seeks to bridge this gap by exploring the application of CNN-GRU models, specifically for turbofan engines, using the C-MAPSS dataset. The aim was to optimize the CNN-GRU architecture for diverse operational conditions by focusing on both spatial and temporal dependencies. The expected outcomes should substantially contribute to the development of robust predictive maintenance systems, enhancing the prediction accuracy and operational efficiency across a range of industrial applications.

2. Material and Methods

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This study focused on the application of a combined Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) architecture to predict the Remaining Useful Life (RUL) of turbofan engines. The selection of this architecture leverages the complementary strengths of both models: CNN excels in extracting spatial features from sensor data, whereas GRU is adept at capturing the temporal dependencies in sequential engine data, both of which are crucial for accurately predicting engine life. The CNN-GRU model operates in an end-to-end fashion, with the final output being the predicted RUL based on the sensor inputs of the engine.

To evaluate the performance of this model, we used the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dataset developed by NASA. This dataset is widely regarded as a benchmark in RUL prediction research, owing to its complexity and breadth of operational scenarios. C-MAPSS consists of four subsets, FD001, FD002, FD003, and FD004, each representing

distinct operational conditions for turbofan engines. The dataset was divided into training, testing, and corresponding RUL data, enabling in-depth and precise predictive analysis.
Each subset within the C-MAPSS dataset varied in size, with FD002 and FD004 containing twice as much data as FD001 and FD003 because of the greater number of machine IDs included in the former. To account for these differences, each subset was processed individually to ensure that the input data were properly formatted for deep learning models, which require high-dimensional data to facilitate more extensive feature extraction.
A critical step in data preparation is to transform the two-dimensional input data into a three-dimensional format suitable for the CNN architecture. This transformation allows the extraction of additional spatial patterns from the data. Each data sequence was standardized to a sequence size of 50, with 26 features corresponding to 26 columns in the dataset (excluding the machine ID column). The two-dimensional input, therefore, was reshaped into a (50, 26) format, which was then used to determine the batch size during model training. This approach enhances the ability of the model to capture relevant features, thereby improving its capacity to predict the RUL effectively.
The target label for the model is the RUL value at the highest operational cycle for each machine ID. The RUL for each cycle was computed by subtracting the current cycle number from the maximum cycle number and adding the RUL value for each machine ID. This method allowed the model to learn how the RUL decreased with each cycle, enabling more accurate predictions throughout the engine life cycle. The formula used to compute the RUL is :

$$RUL = RUL_{True\ from\ dataset} + RUL_{cycle\_max-cycle} \qquad (1)$$

The results of this calculation produce a graph comparing the predicted value of the RUL against the machine cycle, as shown in Figure 1.

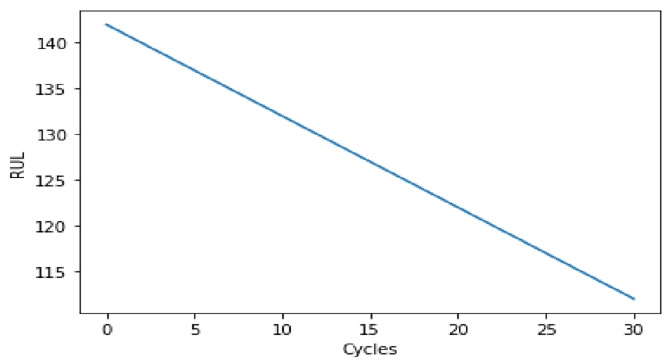

Figure 1. RUL Graph (Source: Author).

The CNN-GRU architecture implemented in this research comprises several key components: the input, CNN, GRU, fully connected, and output layers. The input layer accepts three-dimensional data of size (None, 50, and 26), which represents the sequence length and feature dimensions. These data are processed through the CNN layers, where convolution operations are performed to extract spatial features. Following each CNN layer, a max-pooling operation is applied, which reduces dimensionality while retaining the most important features. To mitigate the risk of overfitting and improve model generalization, a dropout layer was added after each convolution layer.
Once the data passed through the CNN layers, it was fed into the GRU layer. The GRU is responsible for capturing temporal dependencies across machine-cycle sequences, which is critical for predicting the Remaining Useful Life (RUL). The GRU utilizes a gating mechanism to efficiently manage long-term dependencies, thereby enhancing the accuracy of the model in making predictions over extended sequences.
In the final stage, the features extracted by the CNN and GRU layers were passed to the fully connected layer. This layer condenses the features and applies a sigmoid activation function to produce the final output, which is a RUL prediction. This output provides a probabilistic estimation, making it suitable for continuous predictive tasks such as RUL estimation. The CNN-GRU architecture used in this study is illustrated in Figure 2.

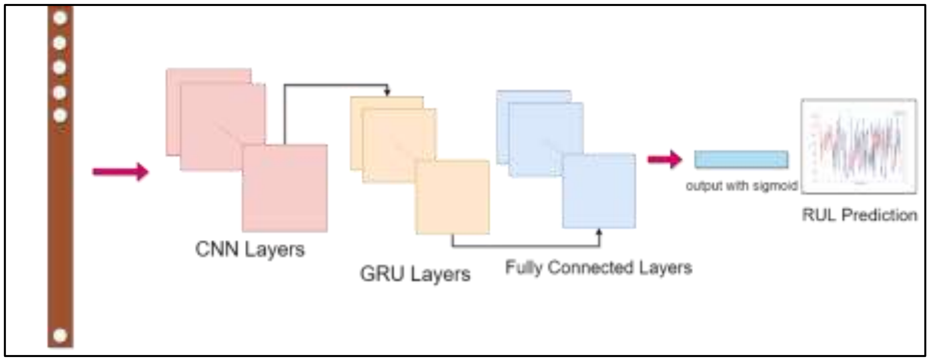

Figure 2. CNN-GRU architecture (Source: Author).

In this experiment, we tested six different combinations of CNN and GRU layers to identify the most optimal architecture for predicting the Remaining Useful Life (RUL). The number of layers in both the CNN and GRU components was incrementally increased to enhance the learning depth and improve feature extraction. The training parameters included a batch size of 512, learning rate of 0.001, and a total of 200 epochs. The Adam optimizer was employed to accelerate the training process and adaptively modify the learning rate to achieve better convergence.
The experiments were conducted on a high-performance server, which enabled faster and more efficient model training than a typical high-specification personal computer. The experimental results, including the total number of parameters trained for each CNN-GRU configuration, are summarized in Table 1. This table provides a clear comparison of the parameter count and model performance for each tested architecture combination.

Model	CNN	GRU	Total Parameter Training
cnn_gru1	1	2	464,769
cnn_gru2	1	3	497,971
cnn_gru3	2	2	440,257
cnn_gru4	2	3	473,409
cnn_gru5	3	2	421,857
cnn_gru6	3	3	455,009

Table 1. Six combinations of CNN-GRU architectures for the experiment.

3. Discussion

Experiments utilizing convolutional neural networks (CNN) and Gated Recurrent Unit (GRU) algorithms were conducted to predict the Remaining Useful Life (RUL) of turbofan engines using the C-MAPSS dataset (FD001, FD002, FD003, and FD004). RUL prediction plays a pivotal role in engine maintenance because it aims to estimate the remaining operational life before engine failure occurs. In recent years, substantial advancements have been made in RUL prediction techniques, with the CNN-GRU architecture standing out because of its ability to analyze both static and dynamic features simultaneously.
Prior to using the CNN-GRU model for prediction, a preprocessing step known as windowing was applied to the raw C-MAPSS data. This method splits data into smaller segments, each of which captures the degradation pattern over time. Windowing simplifies the data sequences, allowing the CNN-GRU model to better learn and process the data. It also reduces the complexity of the dataset, making it more manageable for deep-learning algorithms.
Previous studies have demonstrated the effectiveness of windowing in preparing data for deep learning architectures, particularly for models combining CNN and GRU components (Azyus et al., 2023). The CNN is responsible for extracting spatial features from segmented sensor data, whereas the GRU focuses on learning the temporal dependencies across sequences. This approach is highly effective for capturing degradation patterns in turbofan engines, as observed in the NASA C-MAPSS dataset.
The experiments were performed on a server equipped with standard specifications, including nine cores, 12GB of RAM, and a virtualized AMD Epyc OpenVZ CPU. A total of 200 epochs were used for training with an early stopping mechanism in place to halt the training if no significant improvement was observed in the initial epochs. The server specifications enabled the training process to be conducted efficiently and swiftly without compromising the accuracy of RUL predictions (Azyus et al., 2023).
The findings from this study demonstrate that the CNN-GRU model is highly effective in accurately predicting the machine degradation patterns and Remaining Useful Life (RUL). Figure 3 illustrates a comparison between the actual RUL values and predicted values generated by the CNN-GRU model. In each dataset, the red line representing the predicted RUL closely aligns with the blue line that indicates the actual RUL. Notably, the cnn_gru5 model exhibited the highest performance on the FD001 dataset, whereas the cnn_gru1 outperformed the other models on the FD002 dataset. These results highlight the capability of the model to consistently track the RUL across different datasets, demonstrating its robustness and accuracy.

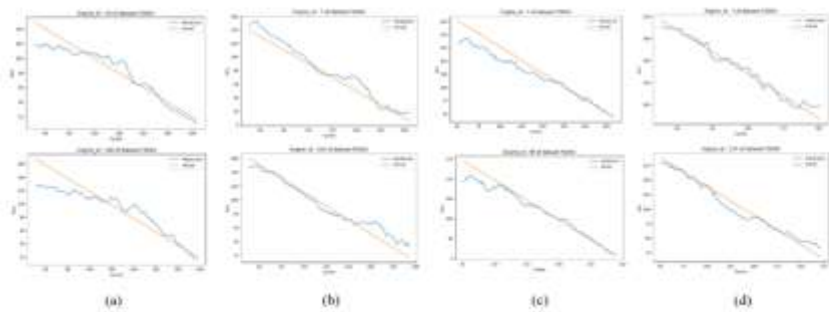

Figure 3. Degradation pattern between RUL data set and experiment (a) result from dataset FD001 using model cnn_gru5 (b) result from dataset FD002 using model cnn_gru1 (c) result from dataset FD003 using model cnn_gru6 (d) result from dataset FD004 using model cnn_gru2 (Source: Author).

The visualization presented in Figure 4 depicts the overall prediction of Remaining Useful Life (RUL) for all machines in the dataset. The graph reveals that the CNN-GRU model effectively captured the degradation pattern, with the predicted RUL consistently aligned with the machine cycles. This result demonstrates the model's ability to not only analyze the spatial features from the sensor data, but also accurately capture the temporal relationships between engine cycles and the progression of performance degradation. This dual capability reinforces the strength of the CNN-GRU model in predicting RUL with high precision across various operational scenarios.

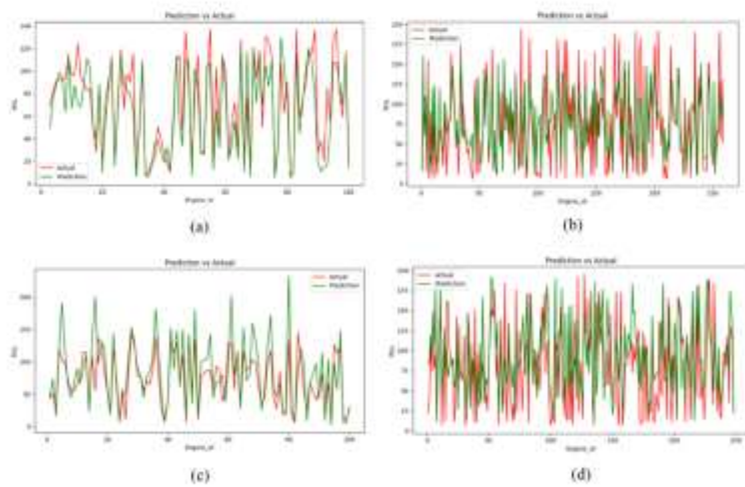

Figure 4. General predictable between RUL data set and experiment (a)FD001 (b)FD002 (c)FD003 (d)FD004 (Source: Author).

To assess the performance of the model quantitatively, the Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) were calculated for each machine across all datasets. The evaluation results presented in Table 2 show the RMSE and MSE values for the various CNN-GRU models tested. The cnn_gru4 model provided the most accurate predictions for the FD002 dataset, whereas the cnn_gru9 model outperformed the other models for the FD003 dataset. For FD001, the lowest RMSE value was achieved by the CNN _gru8 model, indicating its effectiveness in handling datasets with simpler cycles.

Dataset CMAPSS	Model	RMSE	MSE
FD001	model_cnngru8	16.29382515	270.7804565
FD002	model_cnngru4	31.4636097	1014.903076
FD003	model_cnngru9	23.71107292	583.1408081
FD004	model_cnngru5	41.13494492	1722.932373

Table 2. Experimental results for all machines and evaluation values (RMSE and MSE).

These findings are further supported by the results discussed in the Software Impacts section, which demonstrate that CNN-GRU produces more accurate RUL predictions than other deep learning methods, such as LSTM or pure CNN (Azyus et al., 2023). The CNN-GRU architecture excels in training efficiency because of its smaller number of parameters, making it well-suited to handling large datasets such as C-MAPSS without requiring excessive training time, while maintaining high predictive accuracy. This study also compared the performance of the CNN-GRU model with other RUL prediction models, including the Multilayer Perceptron (MLP), Support Vector Regression (SVR), and Relevance Vector Regression (RVR). The comparison, as presented in Table 3, shows that CNN-GRU consistently yielded lower RMSE values than the other models, particularly for the FD001 and FD002 datasets. This indicates the superiority of the CNN-GRU model in managing datasets with dynamic and complex features.

Model	**CMAPSS RMSE MSE**			
	FD001	**FD002**	**FD003**	**FD004**
MLP	37.56	80.03	37.39	77.37
SVR	20.96	42	21.05	45.35
RVR	23.8	31.3	22.37	34.34
CNN	18.45	30.29	19.82	29.16
CNN_GRU	16.29	31.46	23.71	41.13

Table 3. Comparison of CNN-GRU model with other models (Babu et al., 2016).

These findings are in line with those reported in a software impact study, which also demonstrated the superiority of the CNN-GRU model in RUL prediction over alternative approaches (Azyus et al., 2023). Additionally, this research highlights the importance of selecting models that are well-suited to the characteristics of the dataset used. The results indicate that the CNN-GRU is particularly effective for datasets with intricate degradation patterns, such as those found in the C-MAPSS dataset.
The results of this study showed that the CNN-GRU algorithm could successfully predict the degradation pattern and remaining useful life (RUL) of engines in the C-MAPSS dataset. Figure 3 illustrates the comparison between the predicted and actual RUL for each of the four datasets (FD001, FD002, FD003, and FD004). As shown in the figure, the CNN-GRU algorithm can accurately capture the RUL reduction trend for each engine unit. To evaluate the performance of the CNN-GRU algorithm further, the root-mean-square error (RMSE) was calculated for each machine in the four datasets. Table 2 presents the average RMSE values for all machines in the four datasets using different CNN-GRU models. From the table, the cnngru4 model had the lowest RMSE values, indicating that it was the most accurate model for predicting RUL in all four datasets. In addition to comparing the performance of the CNN-GRU algorithm with different models and configurations, the results of this study were compared with those of previous studies that used the same C-MAPSS dataset. Table 3 presents a comparison of the RMSE values obtained in this study with the RMSE values reported in previous studies. As shown in Table 3, the CNN-GRU algorithm performed better than some of the existing methods for predicting RUL. This suggests that the CNN-GRU algorithm is a promising approach to RUL prediction using the C-MAPSS dataset. It is worth noting that the characteristics of each C-MAPSS dataset are different, and that not all methods, machine learning, and deep learning models can be applied to all datasets. Therefore, it is important to select an appropriate model configuration for each dataset in order to achieve the best prediction results. In this study, the cnngru8 model was found to be the most appropriate model for the FD001 dataset, while the cnngru9 model was found to be the most appropriate model for the FD003 dataset.
We also compared the performance of the CNN-GRU with that of other prediction models. Baroud et al. (2024) used a combination of AI techniques, including CNN and GRU, to improve fault diagnosis in predictive maintenance. They demonstrated that this model is effective for processing complex and diverse sensor data. This finding is similar to that of the present study. Mazaev et al. (2021) highlighted the importance of proper estimation in RUL prediction using Bayesian-based CNNs. Their research supports the finding that the CNN-GRU can provide more reliable and accurate predictions.
Hsu et al. (2022) used a temporal convolution-based LSTM model to predict the RUL. They found that capturing temporal patterns is crucial for RUL predictions. This is relevant to the GRU capability in our model, which was shown to capture complex degradation patterns from machine sensor data.
Rivas et al. (2024) developed a prediction system that uses CNN to detect component damage and Bayesian Neural Network to estimate RUL. Approaches such as this show the importance of combining multiple techniques in predictive maintenance, which is also observed in our study.
Pebrianti et al. (2024) demonstrated that the application of CNN-based predictive maintenance in the aviation sector can improve operational efficiency. They found that a CNN could predict engine failure with high accuracy. This further strengthens the effectiveness of CNN for processing complex sensor data.
Habib and Mohamed (2024) also found that model optimization such as CNN-LSTM can significantly improve RUL prediction accuracy. They confirmed that model optimization is essential for achieving better results in prediction tasks.

Overall, this study shows that CNN-GRU is highly effective for RUL prediction in turbofan engines. The combination of a CNN, which is strong in spatial analysis, and a GRU, which is reliable in capturing temporal patterns, results in more accurate predictions than methods that rely on only one approach. Thus, CNN-GRU has great potential for use in various industrial sectors, particularly in complex and challenging environments.

A comparative analysis with existing models shows that our CNN-GRU algorithm performs better than some traditional methods for Remaining Useful Life (RUL) prediction. Research conducted by De Barrena et al. (2023) and Jafari and Byun (2023) also highlighted the advantages of hybrid models that combine CNN and RNN architectures in various applications. This shows that CNN-GRU is a promising approach for RUL prediction, particularly in complex industrial scenarios.

The CNN-GRU model proved successful in predicting the RUL of turbofan engines and has the potential to be adapted to various industrial sectors. By combining the CNN's ability to extract spatial patterns and the GRU's strength in capturing temporal patterns, this model provides more accurate predictions than methods using only one model.

The experiments conducted show that CNN-GRU significantly outperforms traditional prediction models. The model can capture the complex dynamics of machine sensor data degradation. For example, on the FD001 dataset, the cnn_gru5 model achieved an RMSE value of 16.29. This result proves the effectiveness of the model in understanding the complex degradation behavior, which is difficult to predict using methods such as MLP or SVR.

CNN-GRU combines two core elements: CNN to learn spatial patterns from sensor data, and GRU to capture temporal sequences in machine cycles. Initially, the CNN processes two-dimensional input data (sensor values per cycle) and then transforms them into complex features. Next, the GRU layer analyzes these features to recognize the temporal relationship between the performance degradation and operational time.

The use of windowing techniques during data segmentation allows the model to effectively recognize degradation trends within each machine cycle. The ability of the GRU to manage temporal dependencies is essential for predicting when a machine or component will reach end-of-life.

The integration of static and dynamic features in the CNN-GRU provides a significant advantage over other machine learning models that tend to focus on only one aspect. This integration allows the model to capture complex patterns in data from various applications, as noted by Rivas et al. (2024), who observed similar benefits in their work on pump bearings.

CNN-GRU models are also designed to efficiently manage large amounts of data, which is a crucial requirement in industrial settings, where sensor data are numerous and diverse. Research shows that applying dropout techniques to the CNN layer helps reduce the risk of overfitting, thus maintaining model performance even with large datasets. This is reinforced by studies conducted by Pebrianti et al. (2024) and Habib and Mohamed (2024), which show that this training efficiency not only accelerates the model learning process, but also ensures strong generalization across various operational contexts.

The adaptive capabilities of the CNN-GRU also include its robustness to noisy data. Xu et al. (2024) stated that the application of the attention mechanism further enhances the model's ability to focus on important features, thus improving prediction accuracy even in environments that are uncertain and variable. This robustness makes the CNN-GRU particularly suitable for real-world applications, as illustrated by Hsu et al. (2022) in semiconductor manufacturing processes, where sensor readings are often inconsistent.

The flexibility of the CNN-GRU model is also evident from its application in various sectors, including aviation and energy. Jafari and Byun (2023) showed that this model architecture can capture complex degradation patterns in lithium-ion batteries, demonstrating the great potential of this model for predictive maintenance in various industries. The ability of the model to provide accurate RUL predictions supports its implementation in systems in which operational reliability is critical.

The results of this study provide significant advances in industries that implement predictive maintenance strategies. Specifically, in the aviation sector, the CNN-GRU model can be used to monitor aircraft engine performance in real-time, enabling proactive maintenance actions before failures occur. This capability is in line with that expressed by Baroud et al. (2024), who emphasized the importance of advanced AI techniques to improve operational reliability and reduce maintenance costs in complex systems.

Accurate RUL prediction enables early detection of component failures, especially in the automotive industry. CNN-GRU models are positioned to improve degradation forecasting in critical components such as lithium-ion batteries, as demonstrated by Rivas et al. (2024). Their research indicated that the integration of machine-learning models can significantly improve the accuracy of predictive maintenance efforts, thereby minimizing downtime and extending component life.

The flexibility of CNN-GRU models also extends to other sectors such as manufacturing and renewable energy. Narang et al. (2024) highlighted how deep learning techniques improved RUL predictions for ball bearings, showing how the model can prevent unplanned disruptions and ensure smooth operations. This flexibility further strengthens the potential of the model to adapt to various industrial applications and improve the overall operational efficiency.

4. Conclusion

This study demonstrates the effectiveness of the CNN-GRU algorithm in predicting the Remaining Useful Life (RUL) of engines using the C-MAPSS dataset. Through comprehensive testing across four datasets (FD001, FD002, FD003, and FD004), we observed that each dataset exhibited distinct characteristics, indicating that a one-size-fits-all model may not yield optimal

results. Specifically, the cnn_gru8 model achieved the lowest RMSE value for the FD001 dataset, whereas the cnn_gru9 model excelled in the FD003 dataset, confirming their suitability for these datasets.
These findings indicate that the CNN-GRU algorithm successfully captured the degradation patterns of each engine unit, resulting in accurate RUL estimates. Furthermore, this model is more efficient in terms of computational time and cost than traditional methods. It is crucial to tailor model configurations to specific datasets to achieve the best predictive accuracy. Future research should explore alternative configurations and consider increasing the number of epochs beyond the current 200, potentially up to 300 or 500, as this may refine the prediction results and reduce the RMSE values. Overall, this study provides a promising framework for predicting RUL using deep learning techniques, emphasizing the importance of adapting model selection to the unique features of each dataset.

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