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Unsupervised Autoencoders Combined with Multi-Model Machine Learning Fusion for Improving the Applicability of Aircraft Sensor and Engine Performance Prediction

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Abstract: Predicting aircraft engine performance and sensor data is crucial for ensuring safety and optimizing maintenance schedules, which in turn extends the life of aircraft components. Effective prediction improves operational efficiency and is essential for managing safety. This study focuses on estimating the Remaining Useful Life (RUL) of aircraft engines based on the advanced machine learning models, which is critical for scheduling maintenance proactively. Accurate predictions of RUL allow organizations to plan maintenance based on the engine's actual condition rather than fixed intervals, helping to minimize unexpected downtimes and optimize resource use. Our approach integrates advanced machine learning techniques, using autoencoders for feature extraction combined with various predictive models, to enhance the accuracy of RUL predictions. The experimental results demonstrated the effectiveness of the method. This method leverages detailed patterns from sensor data to improve maintenance strategies and increase aircraft reliability and availability. Implementing such predictive analytics makes maintenance operations more efficient and cost-effective, significantly benefiting fleet management and safety.

Keywords: *Component; Unsupervised autoencoder, machine learning;aircraft sensor and engine performance prediction.*

1. Introduction

Aircraft sensor and engine performance prediction are critical fields in aviation, focused on ensuring safety, optimizing maintenance schedules, and enhancing the longevity of aircraft components. Predicting engine performance not only improves operational efficiency but also plays a crucial role in safety management. One of the key aspects of performance prediction in this area is estimating the Remaining Useful Life (RUL) of aircraft engines and other critical components [1][2]. RUL refers to the estimated time or cycles an asset, such as an engine, can continue operating before it reaches a point of failure. Accurate RUL predictions help organizations anticipate when maintenance is required, allowing for proactive planning that minimizes unexpected downtimes, optimizes resource allocation, and extends the component's lifecycle.

In the context of aircraft engines, RUL prediction is especially significant. Engines are subject to high operational stress, with extreme temperatures, pressures, and mechanical loads, making timely maintenance essential. An accurate RUL prediction allows for maintenance to be scheduled based on the actual health of the engine rather than just relying on fixed maintenance intervals. This shift to condition-based maintenance can reduce costs and improve reliability, as maintenance can be performed precisely when needed, rather than prematurely or too late. By understanding and predicting the operational health and lifecycle of engines, organizations can manage their resources more effectively, prioritize maintenance activities, and ultimately improve aircraft availability and reliability.

Historically, aircraft performance and RUL predictions have relied on statistical models and rule-based approaches [3][4]. These traditional methods use mathematical models based on historical failure data and predefined thresholds to predict when an engine or component is likely to fail. While effective to some extent, these methods have limitations. Rule-based models require extensive knowledge of the specific asset's operational characteristics, which can be labor-intensive to acquire and may not always generalize well to different types or models of engines, which are demonstrated in some works [5][6][7]. Moreover, statistical models typically assume linear relationships between variables [8][9][10] , which can oversimplify the complex, nonlinear interactions within an engine's components and sensors. As a result, these models often fail to capture the full range of factors influencing an engine's performance and degradation, leading to less accurate or generalized predictions. Another significant limitation is that traditional models lack the ability to learn from new data dynamically. As an engine operates over time, its wear patterns, environmental conditions, and operational stresses can change, requiring an adaptable approach. With fixed-rule or linear models, these evolving conditions are difficult to account for, leading to reduced accuracy over time. These limitations highlight the need for advanced, adaptable, and data-driven approaches to better predict aircraft sensors and engine performance.

With advancements in artificial intelligence (AI) and machine learning (ML) in many fields [11][12][13], new opportunities have emerged for more sophisticated and adaptable RUL prediction models. Machine learning algorithms can learn complex, nonlinear relationships from large datasets [14][15][16], making them particularly suitable for modeling the intricate interactions within aircraft engines. The effectiveness of them has been demonstrated in many engineering tasks. For instance, Xiong et al. tackled Android malware detection challenges by applying machine learning (ML) and deep learning (DL) techniques with domain adaptation to enhance model generalization [17]. Chen et al. proposed an optimization method for mobile robot delivery systems using deep learning to address challenges in complex, dynamic environments [18].

By processing large amounts of data from aircraft sensors, ML models can identify hidden patterns and trends that may indicate an engine's health and degradation patterns over time. This has led to a growing interest in applying AI-driven models to RUL prediction, where predictive models can be trained on historical sensor data and other operational metrics to make more accurate, data-driven predictions.

Recent progress in deep learning and neural networks has further enhanced the ability to model complex systems [19][20][21]. Autoencoders [22][23], a type of neural network architecture, have proven effective in feature extraction and dimensionality reduction. Autoencoders are especially useful for unsupervised learning, where they can learn compressed, high-level representations of input data. By encoding complex sensor data into lower-dimensional representations, autoencoders can help capture the most relevant features that influence an engine's performance and degradation. However, despite the advancements, machine learning applications in aircraft engine RUL prediction remain relatively limited. The unique challenges in this domain, including the need for high interpretability, robustness against noise, and adaptability to different types of engines and operational conditions, mean that ML models for this purpose are still an active area of research. This paper aims to bridge this gap by developing a comprehensive framework for RUL prediction using autoencoders and machine learning models, combining these methods to enhance predictive accuracy and reliability.

In this paper, we propose a novel approach for RUL prediction that leverages the feature extraction capabilities of an autoencoder and combines multiple machine learning models shown in Figure 1 to achieve higher accuracy. The proposed methodology begins by using an unsupervised autoencoder to generate high-level representations of sensor data. The encoder part of the autoencoder compresses the original sensor data into a set of significant features, which are essential for understanding the underlying health and performance of the engine. These extracted features are then fed into multiple machine learning models, each trained to make RUL predictions based on these high-level representations. To ensure robustness, the predictions from these individual models are then combined. We use a linear regression model to integrate the outputs of these models, assigning optimal weights to each model's prediction based on its performance. This fusion approach allows the final model to benefit from the strengths of each individual model, leading to a more reliable RUL prediction. The final output is an RUL estimate that integrates multiple perspectives on the sensor data, making the prediction both accurate and robust across different operational conditions.

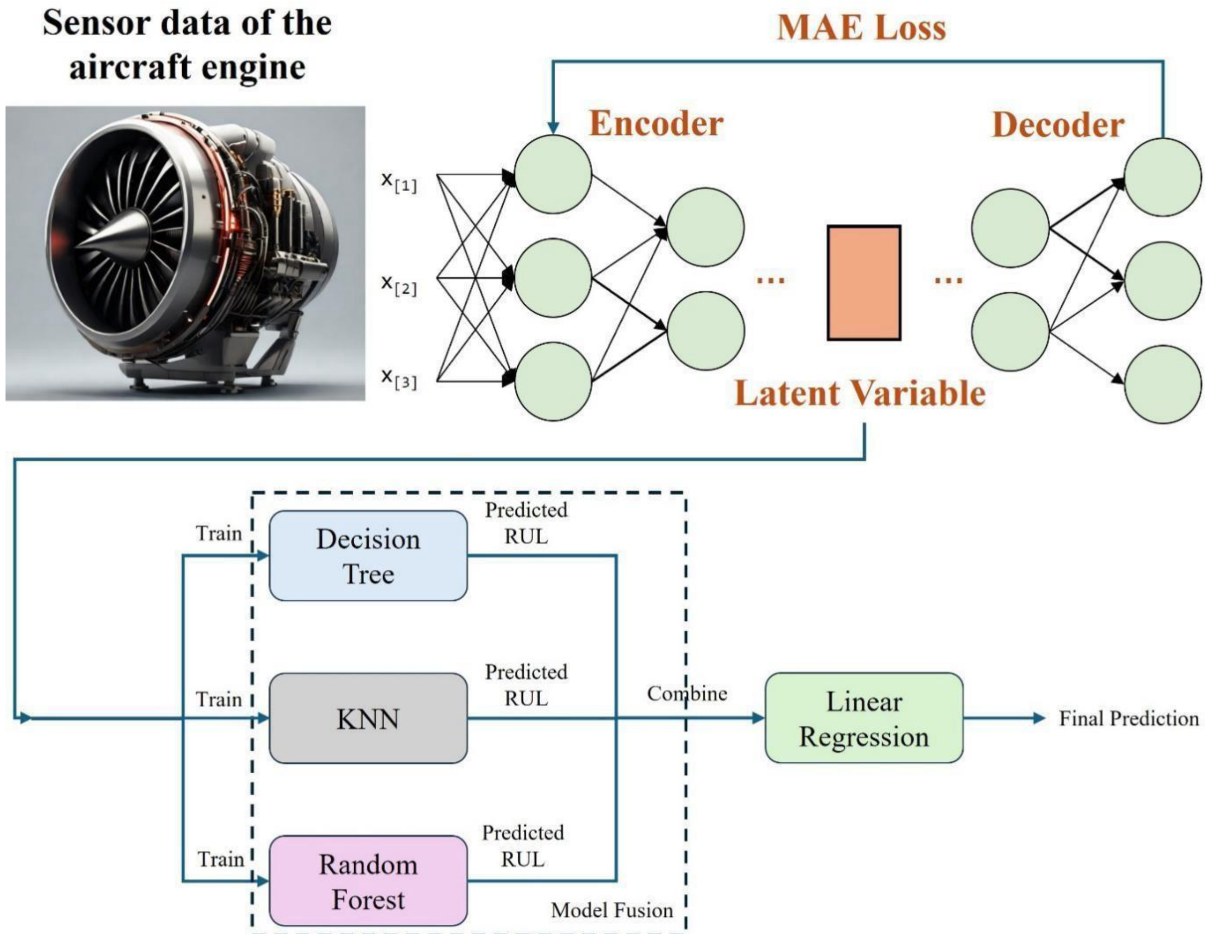

Figure 1. The workflow of the proposed unsupervised autoencoders combined with multi-model machine learning fusion method.

2. Literature Review

2.1 RUL prediction based on machine learning

In the rapidly evolving field of aircraft engine prognostics, the prediction of RUL using machine learning techniques has garnered significant attention due to its potential to enhance maintenance strategies and improve reliability. A variety of approaches have been explored in recent literature, highlighting the adoption of both traditional machine learning and advanced deep learning techniques to tackle this complex problem due to their excellent performance in many tasks [24][25][26][27].

One notable study employs the Long Short-Term Memory (LSTM) network to predict the RUL of aircraft engines, emphasizing the importance of handling high-dimensional sensor data effectively [28]. This method represents a significant shift towards integrating robust machine learning models to better capture the nonlinear and complex degradation patterns often seen in aircraft engine data. Li et al. proposed an ensemble learning-based approach for predicting the remaining useful life (RUL) of aircraft engines. This model combines various base learners (e.g., RF, CART, RNN, AR, ANFIS, RVM, EN) with optimized weights via PSO and SQP. Tested on C-MAPSS data, the approach showed improved robustness and accuracy over traditional prognostic methods [29]. Wang et al. introduced a method for predicting the remaining useful life (RUL) of aircraft engines, combining random forest and Bayes-optimized MLP to handle nonlinearity and high dimensionality in engine monitoring data. Key features were selected using random forest, smoothed with SES to reduce noise, and then fed into an MLP model with optimized parameters. Tested on the C-MAPSS dataset, this approach reduced RMSE by 6.1% on the FD001 test set, demonstrating enhanced RUL prediction accuracy [30].

3. Method

3.1 Dataset preparation

To effectively predict the Remaining Useful Life (RUL) of aircraft engines, we utilized a comprehensive dataset that combines three separate files: PM_test.xlsx, PM_train.xlsx, and PM_truth.xlsx. This merged dataset provides a rich array of information vital for training robust predictive models. The concatenated dataset consists of multiple operational cycles from various aircraft engines, with each cycle capturing sensor readings and operational settings. The dataset includes the following specifics: 1) The dataset contains thousands of individual records spread across numerous engines. Each record includes sensor measurements and operational settings, culminating in a feature set of 24 dimensions. The distribution and box plots of some features are provided in Figure 2 and Figure 3. 2) The features include operational settings (setting1, setting2, setting3) and sensor outputs (s1 to s21). These sensors capture critical performance metrics and environmental conditions affecting the engine's health and performance. 3) we assign the RUL as the difference between the maximum cycle number for each engine (grouped by 'id') and the current cycle number, thereby reflecting the remaining operational cycles before expected maintenance or failure.

Before diving into predictive modeling, the dataset underwent several preprocessing steps: 1) The dataset was cleaned to ensure the removal of any outliers or erroneous entries, and the sensor data were checked for consistency and completeness. 2) Sensor data were scaled using min-max scaling to normalize their range, ensuring that the model is not biased by the scale of different sensors. 3) e allocated 70% of the data for training, 10% for validation and reserved 20% as a test set to evaluate the model's performance.

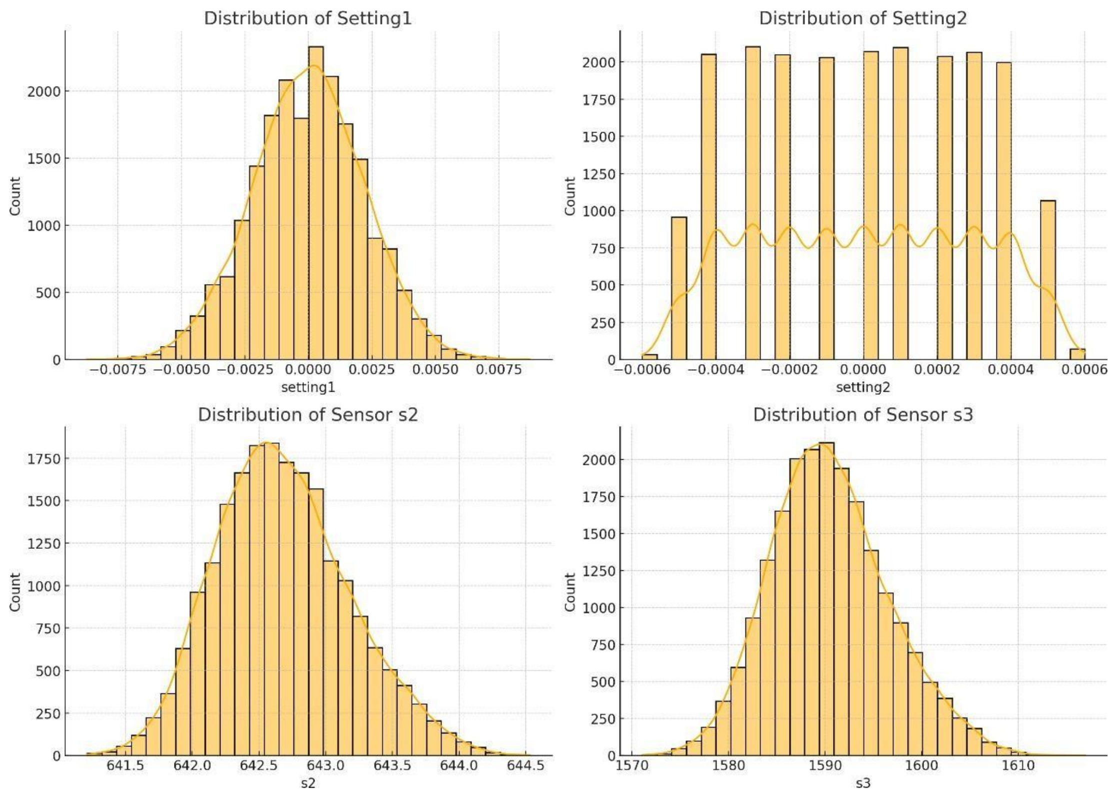

Figure 2. The distributions of some features in this dataset.

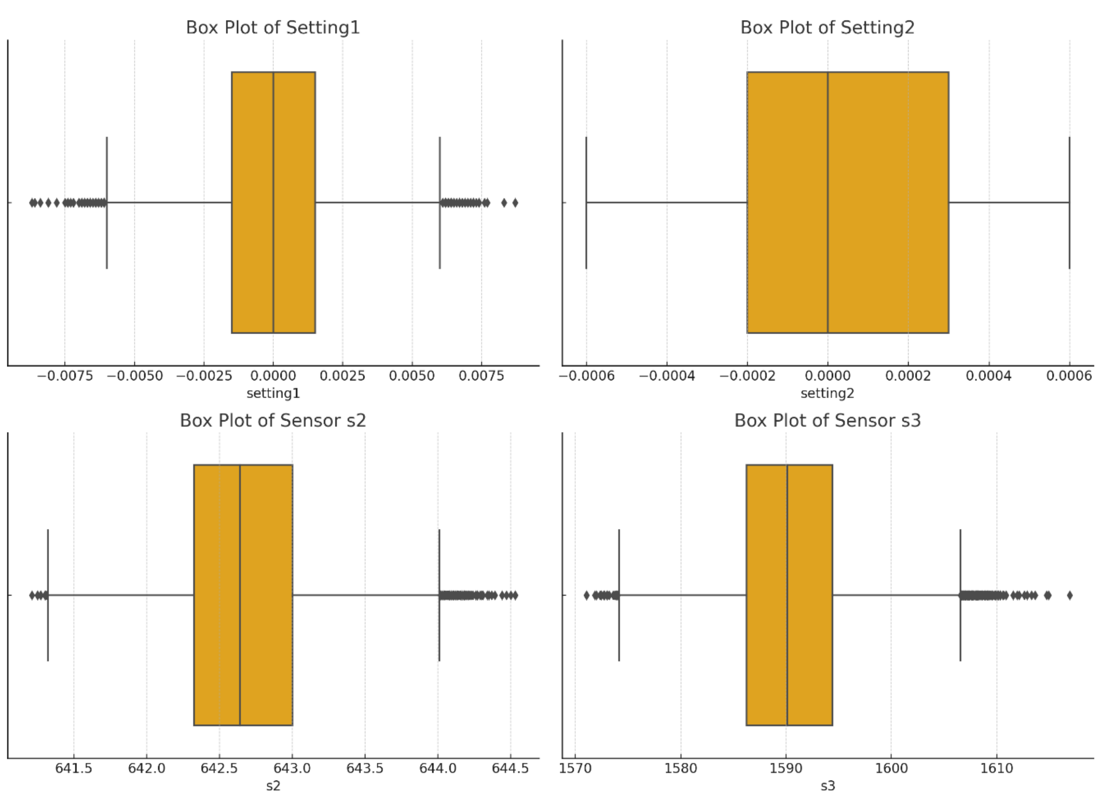

Figure 3. Box plots of some features in the dataset.

3.2 Autoencoder for learning high-level representations

An autoencoder is a type of artificial neural network used to learn efficient representations of data, typically for the purpose of dimensionality reduction or feature learning. Unlike most traditional neural networks that are trained to perform classification or regression tasks by predicting output labels based on input features [31][32][33], autoencoders are designed to reconstruct their own inputs. This means that both the inputs and outputs of an autoencoder are the same. The structure of an autoencoder can be thought of as having two main parts: the encoder and the decoder. The encoder compresses the input data into a smaller, encoded representation, which captures the most significant features of the data. This encoded form is a lower-dimensional version of the input, essentially distilling the information that is most important for reconstructing the input data back from the encoded state. The decoder, on the other hand, takes this encoded representation and attempts to recreate the original input as closely as possible. This process of reducing dimensionality and then reconstructing the data teaches the autoencoder to identify key patterns and correlations in the data.

Autoencoders are trained through a process that involves minimizing the difference between the original input and the output produced by the decoder. This difference is often quantified using a loss function, such as mean squared error, which guides the adjustment of the weights in the network during training. By minimizing this reconstruction error, autoencoders learn to preserve the most important aspects of the input data within the encoded representation. One of the key advantages of autoencoders is their ability to handle unsupervised learning tasks, where no labeled data is available. They can be particularly useful for anomaly detection, where they learn to reconstruct typical data inputs very well but will struggle with inputs that are significantly different from the norm. These differences in reconstruction can then be used to identify anomalous or outlier data points.

In our study, we implemented an autoencoder architecture specifically designed to handle 24-dimensional input data for learning the high-level representation, characteristic of the features derived from aircraft sensor readings. The architecture consists of both an encoder and a decoder section, structured to compress and subsequently reconstruct the input data effectively.

The encoder part of the autoencoder begins with an input layer that receives the 24-feature data. This is followed by a series of dense layers designed to compress the data into a more compact representation: The first dense layer contains 32 neurons and utilizes the ReLU activation function, initiating the process of dimensionality reduction from the original high-dimensional input. The second dense layer further compresses the data to a lower-dimensional space, consisting of 10 neurons, again using the ReLU activation function. This layer effectively captures the most critical features of the data, creating a condensed representation that retains essential information while reducing noise and redundancy.

The decoder section mirrors the encoder in reverse, aiming to reconstruct the original input from the compressed encoded representation: The first layer in the decoder also contains 32 neurons with ReLU activation, beginning the process of expanding the compressed features back towards the original input dimensions. Subsequently, a layer with 64 neurons uses ReLU activation to further enhance the reconstructed data closer to its original form. The final layer of the autoencoder is a dense layer with 24 neurons, employing a linear activation function. This layer outputs the reconstructed data, aiming to match the original 24-dimensional input as closely as possible.

3.3 Multi-model fusion strategy for RUL prediction based on learned high-level representations

3.3.1 Preliminaries of the decision tree

A decision tree is a straightforward yet powerful tool often used in data analysis for making predictions and decisions [34][35]. Imagine it as a tree-like model in decision-making: it starts with a single block, or "node," which branches off into possible outcomes based on different conditions. At each node of the tree, a question is asked about the data that leads to further branches and, ultimately, to the leaves of the tree, where decisions or predictions are made. The paths from the root to the leaves represent decision rules. Typically, decision trees are used in scenarios where data can be split along certain parameters, and patterns can be easily recognized and utilized to predict outcomes. Moreover, decision trees are flexible and can be applied to both numerical and categorical data. They are particularly popular because they require little data preparation, and unlike many other statistical models, they are not influenced by outliers and can handle missing values quite effectively. This makes them an essential tool in various fields where quick and reliable decisions are crucial.

3.3.2 Preliminaries of the random forest

A random forest is an ensemble learning method that operates by constructing a multitude of decision trees at training time and outputting the class that is the majority vote of the individual trees for classification tasks, or the average prediction for regression tasks [36][37]. Essentially, it builds upon the simplicity of decision trees by creating an entire forest of them, working independently and taking the best outcomes from each to produce a more accurate and stable prediction.

The method works by randomly selecting subsets of the training data, building a decision tree for each subset, and averaging the results. This randomness helps to make the model more robust than a single decision tree, reducing the risk of overfitting the training data. Random forests are highly versatile and can be used for both classification and regression tasks, making them applicable in various fields such as finance for credit scoring, medicine for disease prediction, and e-commerce for recommendation systems. The strength of random forests lies in their ability to handle large datasets with high dimensionality and provide assessments of the importance of different features in making predictions.

3.3.3 Preliminaries of the KNN

K-Nearest Neighbors (KNN) is a simple, intuitive, and non-parametric method used for both classification and regression tasks [38][39], but it's particularly popular in classification problems. KNN works by finding the closest data points in the training dataset—known as the nearest neighbors—to a new data point, then making predictions based on these neighbors. For classification, the output is class membership: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). KNN is a type of lazy learning, where the function is only approximated locally, and all computation is deferred until function evaluation. It's highly effective in scenarios where the decision boundary is very irregular. The algorithm is straightforward—calculate the distance from the new point to all known points, identify the nearest k neighbors, and then vote for the most popular output class or average the neighbors in regression problems. KNN can perform well with a small number of input variables (low dimensionality), but struggles with a large number of features (high dimensionality) due to the curse of dimensionality, which complicates the distance calculation between examples.

3.3.4 Multi-model fusion strategy

After extracting refined features through the autoencoder, these are fed into three distinct predictive models: Decision Tree, KNN, and Random Forest. Each model independently assesses the features to predict the RUL. This diversity in modeling techniques enhances the robustness of our predictions, as each model brings a unique approach to handle different aspects of data variance and complexity. To synthesize the insights gathered from each predictive model, we integrate their outputs using a linear regression model. This step involves calculating optimal weights for each predictive model's RUL estimation, allowing us to combine them into a single, more accurate prediction of the engine's RUL. This weighted fusion approach not only improves the accuracy but also the reliability of our predictions, by effectively balancing the contributions of each model based on their performance.

4. Results and Discussion

4.1 The performance of the autoencoder

The figures provided shown in Figure 4 and Figure 5 illustrate the training progression and the reconstruction capability of an autoencoder applied to aircraft engine sensor data, as part of our study to predict the RUL of these engines. Figure 4 shows the training and validation loss curves across 30 epochs. Initially, there is a sharp decrease in loss, indicating rapid learning of the data's underlying patterns. As epochs progress, both training and validation losses stabilize and converge, suggesting that the model is neither overfitting nor underfitting. The closeness of the training and validation loss lines throughout the training process also indicates good generalization capability of the model on unseen data.

Figure 5 illustrates comparisons between the original and reconstructed sensor data for multiple samples. Each subplot represents a single engine's sensor readings, with the original data plotted in purple and the reconstructed data in red. These plots demonstrate that the autoencoder effectively captures the significant fluctuations and trends in the sensor data, which are crucial for the following RUL prediction. Although there are minor discrepancies in peak values, the overall alignment of the reconstructed data with the original data showcases the model's capability to approximate complex sensor patterns.

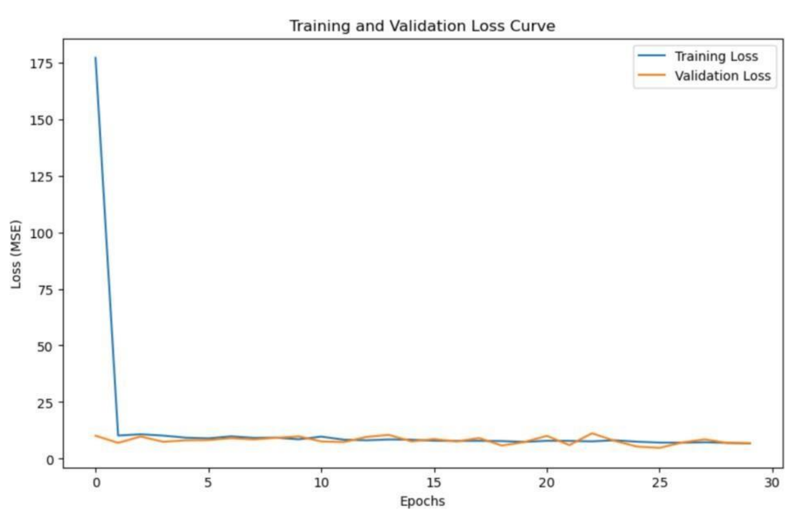

Figure 4. The training curves of the autoencoder.

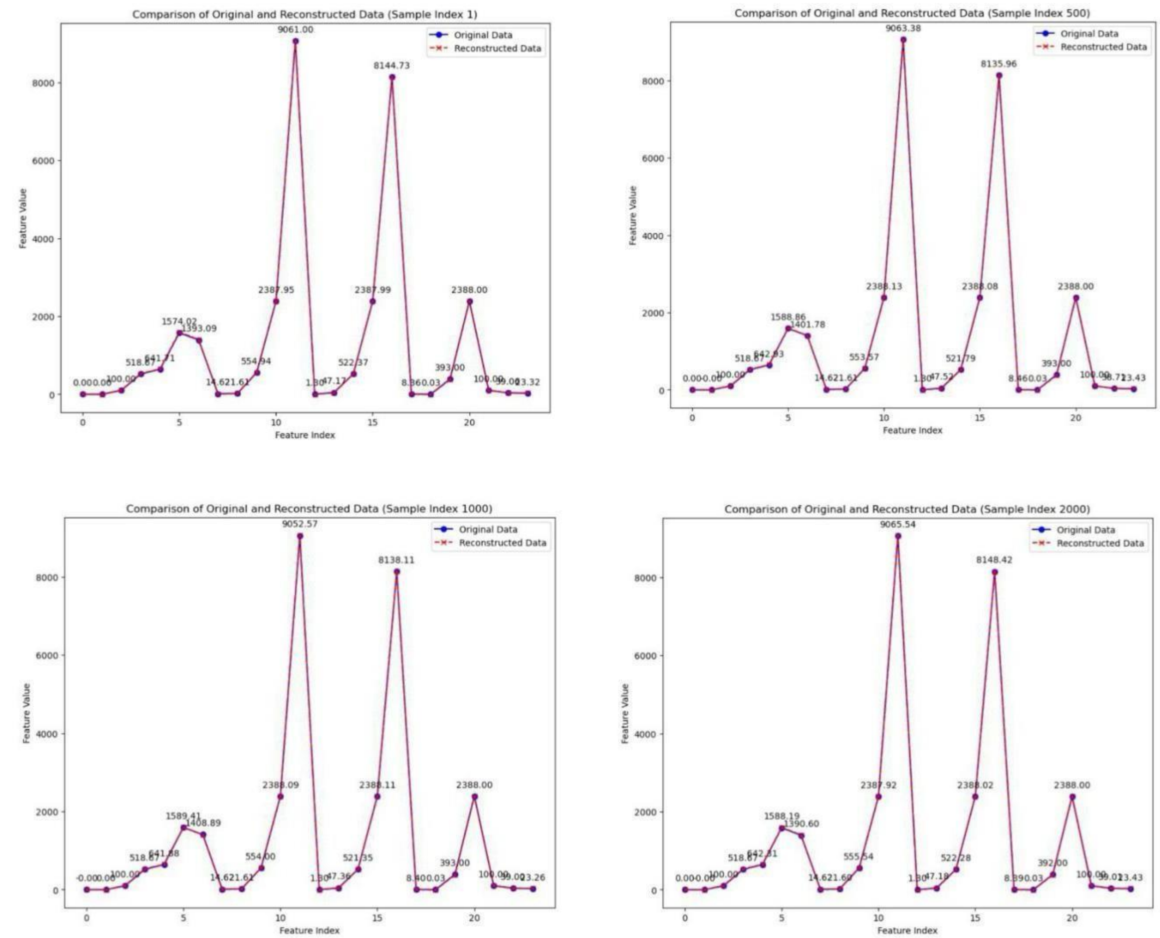

Figure 5. Comparison of original and reconstructed sample data.

Figure 6 shows a visualization of the encoded (latent) layer of our autoencoder, reduced to two dimensions using Principal Component Analysis (PCA). The left plot represents the latent variables for the training dataset, while the right plot shows the latent space representation for the testing dataset. By mapping the encoded layer to two principal components, we gain a clear view of how the autoencoder captures the structure and distribution of the sensor data. Both the training and testing sets display a similar pattern, indicating that the autoencoder is learning consistent, meaningful representations of the data. This consistent clustering also suggests that the autoencoder can generalize well, capturing key features that are not limited to the training data alone.

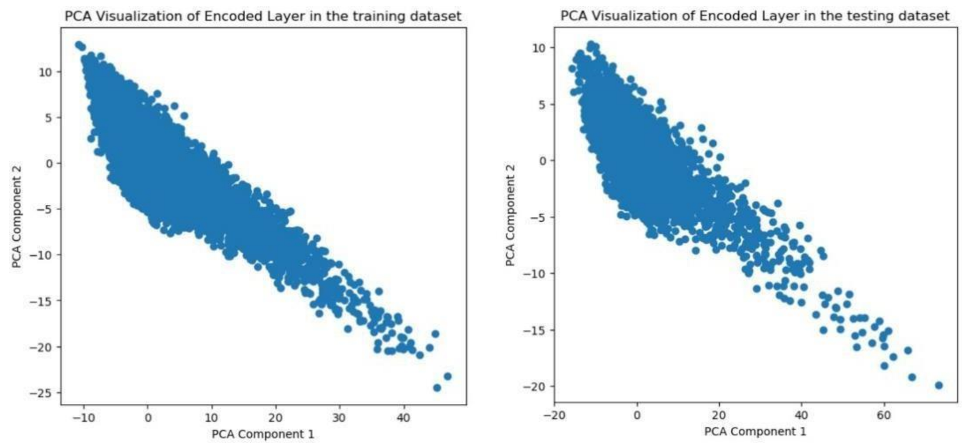

Figure 6. PCA visualization of the encoded layer in the training and testing datasets.

Table 1 illustrates the performance differences between traditional machine learning models and those enhanced with features extracted via an autoencoder for predicting the RUL of aircraft engines. Direct application of traditional models such as Decision Tree, Random Forest, and KNN on the original dataset yielded varying levels of accuracy, with Random Forest outperforming others by achieving a Mean Absolute Error (MAE) of 35.952 and an R^2 of 0.490, indicating moderate predictive accuracy.

In contrast, integrating an autoencoder for feature extraction before applying the same machine learning models showed distinct improvements in several cases. Notably, the Random Forest model combined with autoencoder features reduced the MAE to 34.620 and increased the R^2 to 0.501, demonstrating enhanced predictive capability and better generalization. Similarly, the Autoencoder + KNN model improved upon the standalone KNN, reducing the MAE and achieving a higher R^2 of 0.371.

Table 1. The performance of different approaches in the testing dataset based on the original model and autoencoder-based model.

Model Name	MAE	RMSE	R^2
Decision Tree	52.796	71.284	-0.086
Random Forest	35.952	48.826	0.490
KNN	40.946	54.855	0.356
Autoencoder + Decision Tree	49.476	68.849	-0.043
Autoencoder + Random Forest	34.620	46.769	0.501
Autoencoder + KNN	38.298	52.106	0.371

4.2 The performance of model fusion-based approach

In the scatter plots shown in Figure 7, each model's predictions are plotted against the actual RUL values. A closer alignment of points along the diagonal red dotted line indicates higher prediction accuracy. The Model Fusion-based Approach, which combines the outputs of individual models using linear regression to assign optimal weights, shows the tightest clustering around this line, suggesting it is the most effective in accurately predicting RUL. This method effectively harnesses the strengths of each underlying model, mitigating individual weaknesses and leading to a robust prediction system.

The bar graphs shown in Figure 8 further quantify this observation, where the Autoencoder + Model Fusion-based Approach not only exhibits lower MAE and RMSE but also achieves the highest R^2 value among the tested methods. This reflects not just reduced prediction error but also a greater explanatory power in terms of variance in the data, underscoring the efficacy of using a fusion approach for complex predictive tasks like RUL estimation in aircraft engines. This integrated approach, leveraging a weighted combination of models, clearly demonstrates its superiority in deriving meaningful insights from the nuanced patterns encoded by the autoencoder.

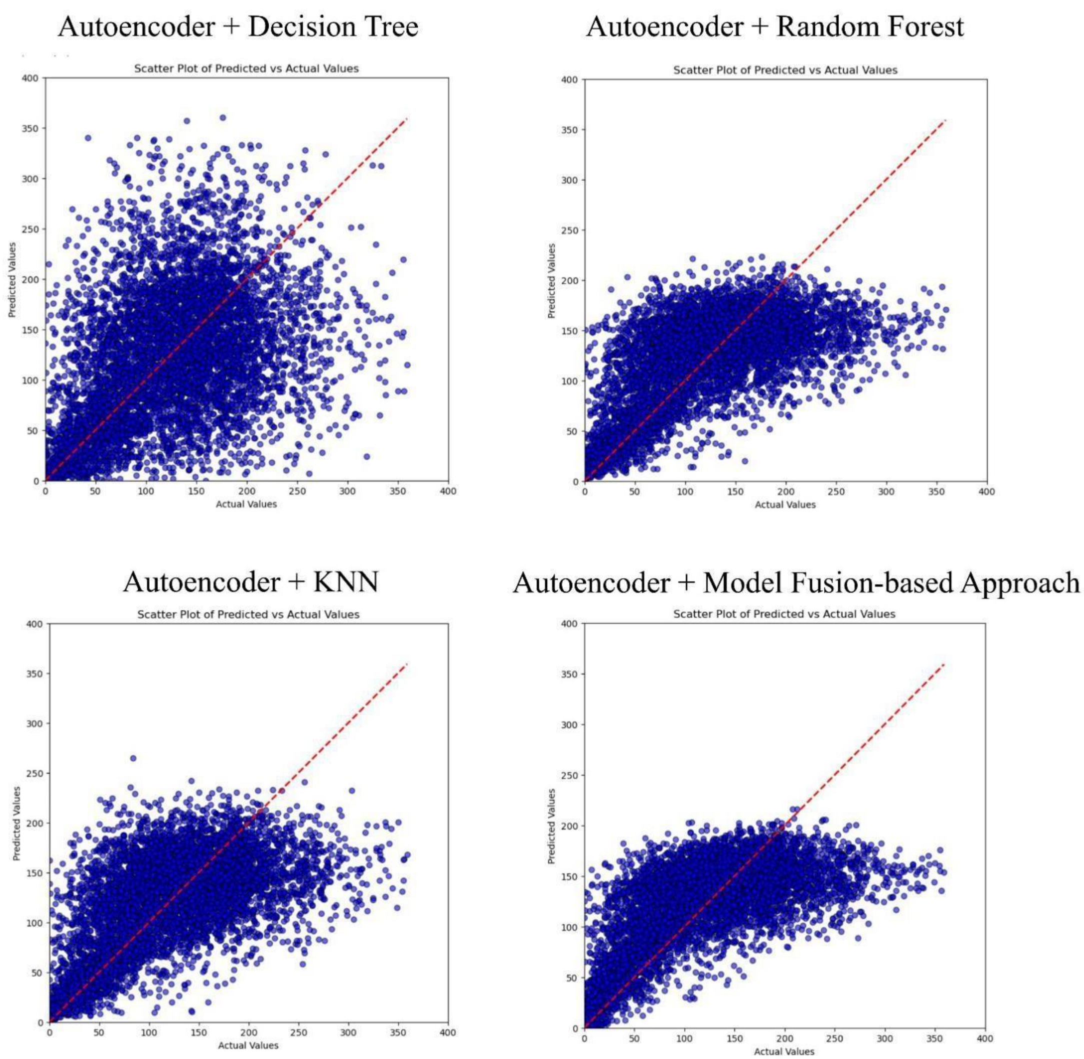

Figure 7. The prediction curves based on different models.

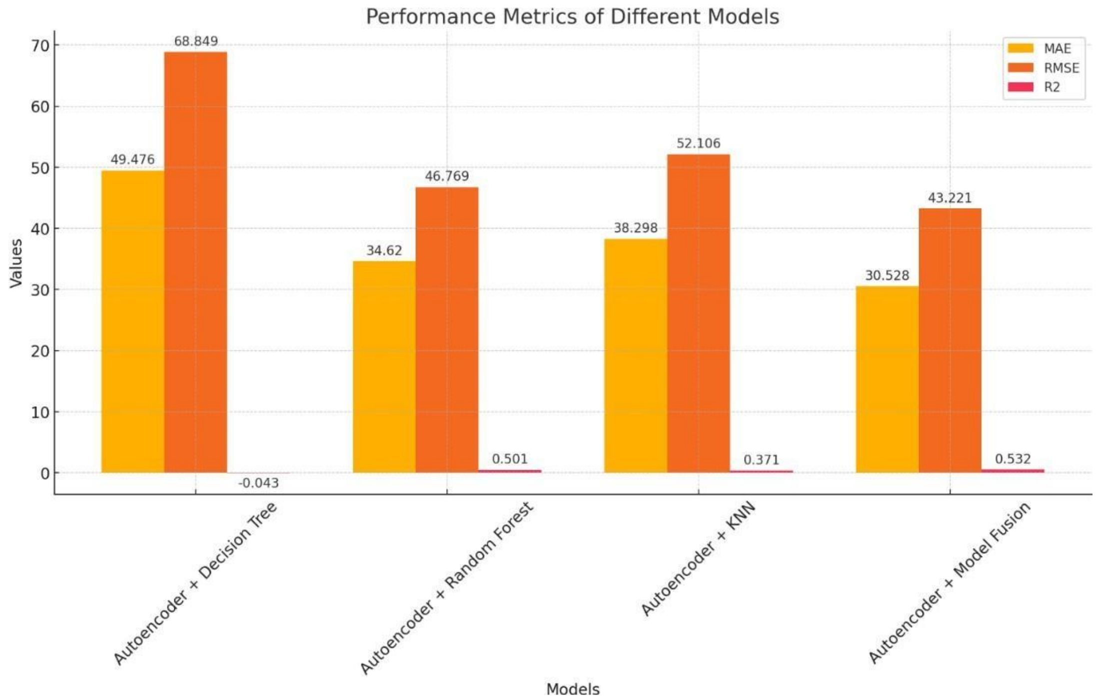

Figure 8. The performance of different approaches in the testing dataset based on the autoencoder-based models.

4.3 The feature importance of the model

Considering the best performance presented by Random Forest in Table 1, we further explored the impact of different features on the results. The provided feature importance visualization shown in Figure 9 graphically represents the significance of various features used in predicting the RUL of aircraft engines, as derived from the sensor and setting data in the dataset. This bar chart ranks the features in order of their importance, calculated based on a predictive model's criteria, which may include metrics like information gain or coefficients in regression models.

In the chart, each feature from the aircraft's sensor data (labeled as s1 through s21) along with engine settings (setting1, setting2, setting3) are displayed with corresponding importance scores. Notably, sensor s14 stands out as having the highest importance, indicating that this particular sensor's readings are most predictive of the engine's RUL. This could suggest that s14 is closely related to critical mechanical functions or stress markers within the engine. Other sensors like s21, s9, and s12 also show relatively high importance, further underscoring their roles in the health and operational status of the engine. In contrast, the engine settings (setting1, setting2, setting3) appear to have the least influence on the predictions, which might indicate that the operational parameters set by these controls are less critical to the engine's immediate functional state compared to the direct sensor readings.

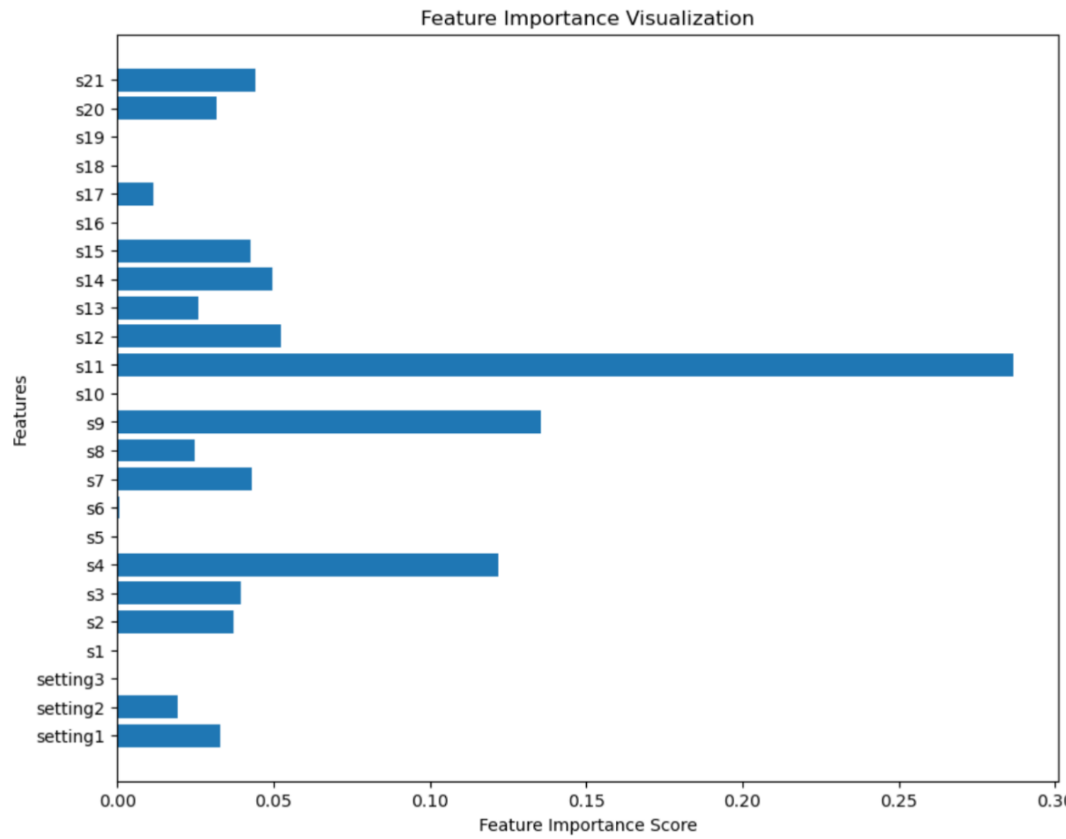

Figure 9. The importance of different features.

5. Discussion

Although the proposed method is effective, it faces certain limitations in its broader applicability. Integrating multiple models—an autoencoder, various predictive models, and a linear regression for final fusion—introduces complexity, making precise tuning and validation essential for optimal performance. Any misalignment among these components could reduce overall prediction accuracy, particularly in diverse operational settings. Additionally, relying on linear regression for model fusion assumes a straightforward relationship between predicted and actual RUL, which may not always align with the complex, nonlinear nature of engine degradation, leading to potential inaccuracies under different conditions.

Moreover, the computational demands of training and maintaining such a sophisticated model are substantial, which presents challenges for real-time application across various systems. Future work could explore advanced domain adaptation strategies to enhance model flexibility due to their excellent performance in various engineering tasks [40][41] , allowing it to adapt more effectively to varied data distributions and evolving conditions. Balancing model complexity, accuracy, and operational efficiency using some advanced methods such as distillation [42]remains essential to ensuring the practical application of this approach.

6. Conclusion

This paper presented a novel approach to predicting the RUL of aircraft engines using a combination of autoencoders and machine learning models. The proposed methodology capitalizes on the strength of autoencoders in extracting meaningful features from complex sensor data, which are then used to train various predictive models. The integration of these models through a linear regression fusion enhances the overall prediction accuracy, allowing for more reliable and precise maintenance scheduling. The results demonstrated that this model fusion approach outperforms traditional methods by effectively handling the non-linear and complex degradation patterns of aircraft engines. However, despite its effectiveness, the approach has limitations such as the need for extensive tuning and the high computational costs associated with training and maintaining the model. Future work should focus on simplifying the model to reduce these demands without compromising predictive accuracy. Additionally, further research into adaptive models that can dynamically incorporate new data and adjust to changing conditions will be crucial for advancing RUL prediction in aviation. The successful implementation of such predictive models has the potential to significantly reduce maintenance costs and improve the reliability and safety of aircraft operations.

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Author Contributions

Tong Zhou contributed to the conceptualization, methodology, and implementation of the unsupervised autoencoder framework, as well as drafting the initial manuscript. Guojun Zhang supervised the research, provided critical insights on the multi-model machine learning fusion strategy, and revised the manuscript for technical accuracy. Yiqun Cai handled data processing, experimental validation, and performance evaluation, contributing to the interpretation of results and manuscript refinement. All authors reviewed and approved the final manuscript.

Institutional Reviewer Board Statement

Not applicable

Informed Consent Statement

Not applicable

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon request.

Conflict of Interest

The authors declare no conflict of interest.

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