AMulti-layer Deep Learning Framework for Real-Time Fault Detection and RUL Prediction in Avionics Systems

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To address the challenge of real-time fault detection in avionics equipment, we proposed a comprehensive framework consisting of data , model, and decision layers. Data is collected in real time from multiple IoT sensors and processed based on a standardized framework. The data model layer utilizes three models for electronic equipment anomaly detection, multi-category fault identification, and remaining equipment life prediction . The model layer contains three core modules: (1) an unsupervised anomaly detection model based on stacked denoising autoencoders (SDAEs) to identify early latent faults using reconstruction errors; (2) a long short-term memory network (LSTM-Attention) with an attention mechanism for accurate classification of multi-class faults; and (3) a Wiener degradation process model based on Bayesian updates to achieve probabilistic prediction of RUL. Experiments were conducted based on the NASA C-MAPSS dataset and real flight data provided by partner airlines. The results showed that the framework achieved an F1 score of 0.969 in the anomaly detection task, an average accuracy of 97.2% for multi-class fault classification, and a RUL prediction interval coverage of 91.3%. After quantization and compression, the model inference latency was only 18.3 milliseconds, meeting the stringent requirements of airborne equipment for lightweight and real-time performance. This method not only improves the economy and safety of aviation maintenance but also provides an interpretable, low-latency end-to-end solution for intelligent health management.

Povzetek: Predlagan je večplastni pristop za sprotno zaznavanje in napovedovanje okvar avionike iz podatkov senzorjev, ki z nizko zakasnitvijo izboljša varnost in učinkovitost vzdrževanja.

1 Introduction

The development of the aviation industry is not only related to the well-being of the people, but also to national security. Therefore, a large number of studies have focused on improving the stability and efficiency of avionics equipment [1] . Nowadays, the integration and integration of avionics equipment are constantly improving, which has promoted the transformation from traditional flight mode to intelligent flight mode. However, this has led to the problem of complexity, with a significant increase in the frequency of failures, the diversity of failures, and the difficulty of diagnosis. In the traditional maintenance mode, avionics equipment is often inspected and repaired regularly. However, in the highly integrated avionics equipment system, this method has become ineffective today because any failure of any electronic equipment may cause a serious aviation crisis and cause huge economic losses. Therefore, in this context, how to monitor and diagnose avionics equipment in real time has become a new trend in the development of the avionics field [2] .

During flight, avionics equipment must maintain high-intensity operation and avoid failures. However, during these intense and prolonged flights, avionics equipment is prone to hidden failures and performance degradation, which traditional maintenance methods are unable to identify. Therefore, to advance modern avionics systems with high safety and availability, we must build a more intelligent, real-time, and accurate fault analysis and detection system.

In this research context, intelligent maintenance and inspection based on data-driven methods using a large amount of collected avionics equipment information has become a new research trend [3] . Traditional fault analysis often relies on expert experience and fault detection analysis, or through aviation failure mode and effect analysis. These methods have obvious shortcomings compared to data-driven methods. They often require human participation and cannot achieve real-time monitoring. Data-driven methods can obtain certain patterns from the operating data of massive equipment, thereby performing real-time monitoring during the operation of the equipment. Relying on sensor monitoring data obtained from the database, historical maintenance records, and records of the aviation health management system to infer possible fault causes and provide timely feedback to engineers can greatly reduce the workload of engineers and improve the stability of aviation operations [4] .

On the other hand, with the rapid development of 5G communication, edge computing and digital twin technology, the operation of avionics systems is evolving in the direction of implementation. However, this trend runs counter to the lag of fault detection. With the real-time nature of avionics systems, fault detection always relies on manual analysis and judgment, which is a lag and cannot support the real-time operation of avionics systems. Regarding the analysis of avionics equipment fault data, research at home and abroad has made certain progress. For example, flight data recording systems have been deployed and operated in most airlines. Such systems can quickly read data from flight process recorders and combine them with real-time data transmitted by the status monitoring system to realize the collection of key module data during aircraft operation [5] . On the other hand, a large number of studies use big data analysis technology to collect and manage avionics equipment fault data. However, the existing research system still has many deficiencies. The first is the data island problem, because the data of different airlines are isolated and exist in different departments and different flight systems. Some studies often use traditional suppression-based methods for analysis and judgment based on large amounts of data. This approach does not take advantage of the advantages brought by big data. On the other hand, the generalization ability of this method is also insufficient. It is difficult to switch and transfer between different data sources [6] .

To address the challenges of the aforementioned research, this paper, based on a machine learning approach and a data-driven approach, constructs an optimized framework for avionics equipment fault data analysis and predictive maintenance. This framework employs a three-layer architecture. The first layer is the data layer, which collects and processes data from numerous IoT sensors and avionics systems. The second layer is the model layer. We incorporate deep learning models to build a real-time analysis system and enhance the model's efficiency through the use of edge devices. The third layer is the decision layer. The model layer's predictions are presented to users through visualization, allowing them to independently decide whether to accept the fault.

Despite the progress made by deep learning in equipment health management, existing methods still have significant shortcomings in multi-task collaborative modeling, cross-domain generalization capabilities, and real-time deployment feasibility. Therefore, this paper proposes the following core research question:

"Can a unified multi-layer deep learning architecture be constructed to achieve high-precision fault detection, fault type classification, and remaining useful life (RUL) prediction while ensuring low latency, and maintain robust performance on various avionics system datasets?"

To address this question, this paper designs a novel multi-task temporal network and verifies its effectiveness and practicality through systematic experiments on C-MAPSS, XJTU-SY, and a self-built real flight dataset.

The model constructed in this paper can significantly improve of avionics equipment, improving the timeliness of fault detection. This shifts from a traditional experience-based approach to a data-based one. From a safety perspective, this method can effectively provide early warning of avionics equipment failures, reducing the incidence of in-flight failures. From an economic perspective, it can shorten maintenance cycles.

2 Related works

2.1 Avionics equipment fault detection technology

The evolution of avionics fault detection technology from traditional experience-based to intelligent has gone through a long period of time. In the early days, it mainly relied on basic fault detectors and the experience of maintenance personnel, and performed fault detection through manual observation, signal detection, and replacement methods. This method has the characteristics of low timeliness [7] . Poor accuracy and high reliance on experience. Therefore, with the rapid development of information technology in China, this method has been eliminated. Currently, it mainly relies on intelligent methods. Scholars have tried to build a systematic detection method. For example, Kabashkin I et al. [8] explored the construction of an expert system in their research. To conduct systematic fault detection, thereby avoiding the high cost and time waste brought by traditional exhaustive and pseudo-exhaustive methods. Other studies pointed out that avionics systems have highly integrated circuits. The vector generation during testing is complex and costly, so the construction of such an expert system requires the construction of a strong expert system. Ali N, Hussain M et al. [9] proposed automatic test equipment in their research, which can be used for offline testing of avionics. Magliano E et al. [10] pointed out in their research that this type of offline electronic equipment can be combined with standard test procedures to efficiently complete the power-on self-test of electronic equipment, and the signal excitation and response data collection process provides a feasible method to a certain extent. However, this type of intelligent algorithm often constructs a correspondence between equipment failure and equipment symptoms based on data, and cannot dynamically perceive problems during the operation of the equipment. In recent years, Zeng ZY et al. [11] proposed a full-process monitoring system for electronic equipment, promoting the transformation of avionics equipment from post-detection to in-operation monitoring, and promoting the development of early warning of avionics equipment failures. Das O et al. [12] showed in their research that this full-process real-time monitoring fault monitoring system has extremely high sensitivity for analyzing equipment failures, sudden equipment aging, and sudden accidents.

2.2 Data-driven

At present, the data-driven approach to avionics fault detection has become a new trend. This method avoids relying on precise physical models and achieves real-time prediction and early warning of faults by mining the potential patterns and laws in historical data. In terms of data collection, a large number of aircraft are now equipped with a variety of sensors, which provides a basis for the feasibility of research. Wu ZJ et al. [13] pointed out in their study that more than 50% of aircraft have achieved automatic collection of equipment status information and maintenance information on the fuselage through the Internet of Things and automatic identification technology. In terms of data processing, Ranasinghe K et al. [14] provided a method system for aviation information data processing and a set of feature extraction methods for aviation data. In the process of analysis and processing, Hapka R et al. [15] proposed using knowledge vector sets to improve the classification of radar received faults. Compared with the traditional experience-based method, it achieved a better accuracy. BOULKROUNE A et al. [16] used the random forest algorithm and then analyzed the simple feature importance method to assist in finding the fault experiment when a multivariate fault occurred in the communication module. The results showed that this feature importance-based method achieved an improvement in accuracy compared with the traditional experience-based and rule-based method. f used a long-term short-term neural network to analyze continuous aviation failure data and identified potential failure points through anomaly detection. These failure points were confirmed to exist in practice, demonstrating the effectiveness of time series data analysis in aviation data processing. Although data processing-based methods are highly feasible, they suffer from poor data interpretability and difficulty in data collection.

2.3 Predictive maintenance strategy

Currently, predictive maintenance strategy has become the core method of sample inspection in modern aviation systems, which can timely identify equipment maintenance needs through equipment monitoring and prediction.

Raza A et al. [17] systematically explained in their research that the basis of maintenance prediction technology relies on a large number of sensor networks, big data platforms and machine learning technologies. The combination of big data and machine learning algorithms can realize real-time analysis of data and provide early warning before a failure occurs. In terms of models, BOULKROUNE A et al. [18] used the Micro-Merck distribution and degradation model to predict the life of electronic components. However, this study was carried out under strict assumptions and is difficult to implement in a practical environment. Dong L et al. [19] used the Markov process and Bayesian network to build a dynamic maintenance prediction system. The maintenance strategy is adjusted according to the real-time status of the equipment. However, this model can only achieve classification. Piumatti D et al. [20] used a comprehensive prediction method to combine the fault prediction model with the maintenance cost model and the aviation planning model to build a multi-objective optimization strategy. However, this goal focuses on achieving a comprehensive optimal solution and cannot achieve the freedom of aviation fault prediction. Gao C et al. [21] introduced digital twin technology into aviation fault detection for the first time. By building simulated equipment to simulate fault scenarios, faults can be predicted to a certain extent. However, this method also faces the problems of low feasibility and weak interpretability.

Table 1 provides a systematic cross-sectional comparison of existing representative research methods, covering four key dimensions: datasets used, task scope, performance metrics, and method limitations.

Table 1: Research summary table

Dataset	Task Scope	Key performance indicators (accuracy/error, etc.)	limitation
C-MAPSS	RUL Prediction	RMSE: 12.3	Only applicable to single failure mode; does not consider multi-sensor heterogeneity.
PHM 2008 Challenge	Fault Detection + Classification	Accuracy: 92.5%	Relies on manual feature engineering; has weak generalization ability.
NASA Turbofan	RUL Prediction	MAE: 8.7 cycles	The model is highly complex; training time is long; and an online update mechanism is not integrated.
Self-built industrial bearing dataset	Fault detection	F1 score: 0.89	Small dataset size; lack of public benchmark validation
C-MAPSS + XJTU-SY	Multitasking (Detection + RUL)	RUL MAE: 9.1; Detection Acc: 94.2%	Unhandled cross-domain scenarios; sensitive to noise

3 Research methods

The model constructed in this paper aims to achieve dynamic perception of the operating status of avionics equipment. By identifying anomalies early during a failure and monitoring the remaining mission life of the electronic equipment, this paper constructs a multi-layered, multi-model fusion framework for intelligent fault prediction and predictive maintenance. This framework is based on a data-driven philosophy and combines information processing technology with deep neural network technology. This forms a complete technical chain from raw data sensors to final, innovative decision-making. The framework model constructed in this paper aims to provide high-precision fault identification capabilities, maximize the quantification of uncertainty, and provide aviation maintenance personnel with interpretable and reliable early warning signals.

As shown in Figure 1, this paper constructs a three-layer framework. The first layer is the data acquisition and preprocessing layer, which primarily uses multi-sensor sensing and performs data denoising and standardization. Principal component analysis is also performed on the data to achieve dimensionality reduction for high-dimensional data. In the second layer, we use an intelligent diagnostic model. This module, based on an unsupervised learning anomaly detection module using autoencoders, is used to identify early hidden faults. This module combines an attention mechanism with long-short-term neural networks to achieve accurate multi-category classification. The third layer is the prediction and decision layer. We combine a Bayesian degradation model with monitoring data to update the parameter distribution, thereby achieving a probabilistic prediction of service life. This model implements two functions: fault identification and accurate classification, and prediction of the service life of avionics equipment.

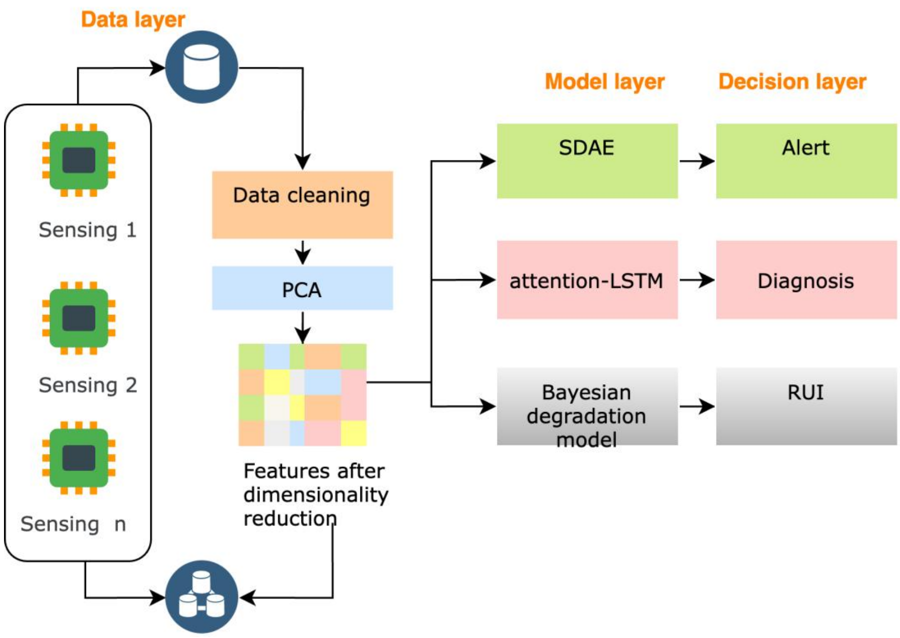

Figure 1: Model framework

3.1 Data collection and preprocessing

During flight, densely deployed IoT sensors collect a large amount of avionics data. This data contains a wealth of information, including the current, voltage, and inertia of power modules, the speed and acceleration of test units, the signal strength of communication circuits, and the temperature of chips. These data are characterized by large data volumes, high dimensions, and severe noise interference. Therefore, we first preprocessed and extracted features from the data. We assume that the raw sensor data is $X \in \mathbb{R}^{N\times M}$, we use n to represent the sampling point of time, m to represent the number of sensor channels, and j to represent the original signal of the sensor channel $x_j(t)$, for these data, we first use median filtering to remove the noise in the pulse data. Specifically, as shown in Formula 1 [22]

$$\hat{x}_j(t) = \mathrm{median}\big(x_j(t-k), \dots, x_j(t), \dots, x_j(t+k)\big) \quad (1)$$

In formula 1 , k is used to represent the half-width of the sliding window. This parameter is used to control the degree of smoothing. $\hat{x}_j(t)$ It represents the filtered signal value after processing. We set the signal value of the jth sensor at time t to be$x_j(t)$, the time window size is $2k+1$, $\hat{x}_j(t)$ represents the filtered data. In addition, for the case of temporary loss of sensor data or data disconnection, we use linear interpolation to fill the gap. We standardize the processed data. Specifically, as shown in Formula 2 [23]

$$z_j(t) = \frac{\hat{x}_j(t)-\mu_j}{\sigma_j}, \quad \mu_j = \frac{1}{N}\sum_{t=1}^{N}\hat{x}_j(t), \quad \sigma_j = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(\hat{x}_j(t)-\mu_j)^2} \quad (2)$$

In Formula 2 , we use$z_j(t)$ To represent the th channel at time t after normalization.μ_j ,σ_j They represent the mean and standard deviation in the time series dimension respectively. After standardization, the data is delimited to a certain range. The difference in dimension is eliminated and Nrepresents the total amount of data[24].

After data preprocessing, we perform feature extraction. The features we construct mainly include mean, variance, skewness, kurtosis and zero-crossing domain. These features can describe the stability and dynamic changes of the signal. In terms of frequency, we use the Fourier transform feature, as shown in Formula 3 [25]

$$\mathrm{STFT}_j(t,f) = \int_{-\infty}^{\infty} z_j(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau \quad (3)$$

In formula 3 we use $z_j(\tau)$ To represent the time domain signal of a channel. $w(\cdot)$To express. The time window function is used to localize the time range to limit the analysis interval. Use $e^{-j2\pi f\tau}$ To represent the exponential basis function used to realize the frequency decomposition, $\mathrm{STFT}_j(t,f)$ The representative frequency output represents the frequency f time-frequency diagram in the time range t. In addition, we also considered multiple frequency-related features, including the center of gravity of the spectrum to represent the frequency of concentrated energy. The drift of this feature indicates the wear of the mechanical device, and the frequency bandwidth is used to reflect the discrete degree of the frequency distribution. The spectrum sound is used to represent the degree of uncertainty of the signal, and the quotient is used to quantify the uncertainty. The increase of this indicator is often related to the occurrence of abnormalities. After feature extraction, we performed principal component analysis, which reduced the dimension of all extracted video feature vectors. The principal components with a cumulative contribution of more than 95% are retained, and the other principal components are removed. The final result is $f_{t'} \in \mathbb{R}^d d \ll D\$$,These results are that low-dimensional representation of high-dimensional features reduces the complexity of the data.

3.2 Unsupervised anomaly detection based on stacked denoising autoencoders

In this section, we aim to detect electronic equipment failures. However, in real-world data, the vast majority of the data space is normal, with only a very small number of failures. These failures are numerous and diverse, making it expensive to obtain labeled data. Based on this, we developed an unsupervised training method. Therefore, this section proposes a novel approach that uses stacked denoising autoencoders and combines them with unsupervised data for anomaly detection. The core of this method is to train the model using a large amount of positive sample data, allowing it to learn the underlying behavioral patterns of these positive samples. Once the model encounters negative samples, it exhibits behavior that deviates from normal patterns, indicating potential failures. This triggers an early warning. This reconstruction error-based approach can significantly alleviate the problems caused by sample imbalance.

The autoencoder used in this paper is composed of an encoder that can compress high-dimensional data into a low-bit latent space and a decoding part that decodes the data line. In this model, the input feature vector can be expressed as f_t , in the encoding process, there are two hidden layers. After the first hidden layer, we get formula 4

$$h^{(1)} = \sigma(W^{(1)} f_t + b^{(1)}) \quad (4)$$

In formula 4, we have $W^{(1)} b^{(1)}$ Use to represent the weight vector and bias vector of the model, and use $\sigma(\cdot)$To improve the nonlinear expression ability of the model. Then we performed the second layer encoding. As shown in Formula 5 , $W^{(2)} h^{(1)}, b^{(2)}$the parameters representing the encoding of the second layer are[26].

$$h^{(2)} = \sigma(W^{(2)} h^{(1)} + b^{(2)}) \quad (5)$$

Through this structure, we can obtain a deep feature representation

The encoding process includes two embeddings, the core purpose of which is to extract the high-dimensional features implicit in the data and obtain the feature representation implicit in the data.

The decoding process is to use a multi-layer neural network to convert the deep embedding representation into a high-dimensional feature vector $\sigma(W^{(d1)} z + b^{(d1)})$. Then we perform the first-layer feature mapping and then use $\sigma(W^{(d2)} \hat{h}^{(1)} + b^{(d2)})$ the second-layer feature mapping . After two layers of mapping, we get the final reconstruction result.

The principle of the encoder-decoder structure is that if the input data is normally distributed, the feature vector output by the encoder and decoder process should be very close to the original feature. $\hat{f}_t$represents the output feature, and $W^{(o)} \hat{h}^{(2)}$, $b^{(o)}$represents the parameters and bias terms respectively.

$$\hat{f}_t = \sigma(W^{(o)} \hat{h}^{(2)} + b^{(o)}) \quad (6)$$

In order to enhance the robustness of the model, we introduce noise into the training data and superimpose white noise on the original data, as shown in Formula 7.

$$\epsilon \sim \mathcal{N}(0, \delta^2 I), \quad \tilde{f}_t = f_t + \epsilon \quad (7)$$

$\tilde{f}_t$The features after mapping $\epsilon$are noise. The training goal is to reconstruct the original clean data from the contaminated data. This noise-based recovery training allows the model to not only learn a simple identity factor but also learn to ignore the noise components in the data and focus on the implicit structure and patterns in the data. This improves the model's robustness to noise and enhances its ability to observe implicit patterns in normal data.

The goal of this part of the training is to minimize the reconstruction error, which is Formula 8.

$$\mathscr{L}_{AE} = \frac{1}{T} \sum_{t=1}^{T} \|f_t - \hat{f}_t\|^2 + \lambda\left(\sum_l \|W^{(l)}\|_F^2 + \sum_l \|W^{(dl)}\|_F^2\right) \quad (8)$$

In formula 8 , $\mathscr{L}_{AE}$represents the loss function. The first term we use is the mean square error $\sum_{t=1}^{T} \|f_t - \hat{f}_t\|^2$ to measure the difference between the original input and the reconstructed input. We use regularization $\lambda\left(\sum_l \|W^{(l)}\|_F^2 + \sum_l \|W^{(dl)}\|_F^2\right)$to limit the complexity of the model and avoid overfitting. At the same time, we use hyperparameters λ To quantify the balance between policy degree and similarity degree , T represents the total number of samples.

3.3 Multi-category fault identification

In this section, we provide an anomaly detection method that can determine whether avionics equipment has deviated from its normal state. These methods not only determine whether a fault has occurred, but also analyze the specific type of fault. For example, common fault causes include power module failure, overvoltage, and communication circuit failure. In Section 3.2, we implemented anomaly early warning triggering. In Section 3.3, we implemented a high-precision fault classification module to identify specific fault categories, providing reliable reference for engineers. Therefore, in this section, we designed and implemented a long-term short-term neural network based on the attention mechanism to accurately identify multiple fault categories.

Fault identification relies on sequential networks. For example, temperature anomalies often begin with a slow increase, followed by a restart as voltage and temperature rise and fluctuate. Long- and short-term neural networks offer a natural advantage in analyzing this type of data.

Therefore, we use long short-term neural networks to process long sequence data. However, this process has its shortcomings.

Final hidden state output by the long short-term neural network h_T It can be considered as the feature representation of the entire time series, which is the sum of information at all time steps. However, not all data points in the entire time series are equally important. Data at the critical point of failure should be given higher weight. Therefore, we added an attention mechanism to the long-term short-term neural network to explicitly learn the weights of the model at different time steps. We use the attention mechanism to calculate the attention score of each hidden state, as shown in Formula 9 .

$$e_t = v^T \tanh(W_a h_t + b_a) \quad (9)$$

In Formula 9, W_a, h_t, b_a represents the weight matrix, attention matrix and bias term, v^Ttrepresents the specific value, e_t represents the attention score. After obtaining the attention score, we normalize the score to obtain the degree of attention of the model for different time steps . Based on the context score provided by the attention mechanism, we perform weighted summation on all hidden states to obtain an implicit vector that focuses on key information. Specifically, if it is 1 0

$$s = \sum_{t=1}^{T} \alpha_t h_t \quad (10)$$

Formula 10 , we use s To visualize the degree of attention paid by the model to the time series data , $\alpha_t$we represent the attention score. After obtaining the feature output with implicit attention weight, we classify this vector and obtain the final classification result, as shown in Formula 1 1.

$$p = \mathrm{softmax}(W_y s + b_y) \quad (11)$$

In formula 1 1 we use$p = [p_1, p_2, \dots, p_K]$ To express the classification probability of breeding failure, this is a multi-classification problem. Therefore, we use the cross-quotient function as the loss function during training.

3.4 Equipment service life prediction

In order to predict the service life of equipment, we constructed a fusion method based on Bayesian updating and Wiener process. The use of avionics equipment has the characteristics of performance regression and randomness, so this paper uses formula 1 2 to model the performance degradation of avionics equipment.

$$Y(t) = \theta + \beta t + \sigma_B B(t) \quad (12)$$

In formula 1 2 we useβ To represent the performance degradation rate, to simulate$B(t)$ The range of Brownian motion. Thus, the parameters change with time , θ represents the parameter, t represents the time, $Y(t)$ Represents the performance of the electronic device when the threshold is first reached D This means that the electronic device has failed, and the system will generate an early warning. Considering the uncertainty in the use of the device, we introduced the Bayesian framework toβ As a random variable, in a certain model, we use the real-time monitoring data to continuously update its posterior distribution. Finally, we use the updated parameters to calculate the expected performance value of RUL $\mathbb{E}[RUL_t|\mathcal{D}_t]$ Point estimates are presented as hypothesis tests, and 90% confidence intervals are drawn to obtain an appropriate range.

In this study, the prior distribution of the Wiener degradation model was not arbitrarily set, but rather statistically derived from performance degradation data accumulated from historical flight missions and ground tests of similar avionics equipment, thus possessing a clear engineering experience foundation. Specifically, we first analyzed the degradation trends of a large number of similar devices, and based on this, set an initial degradation rate range as prior knowledge. During actual flight, after each complete monitoring cycle (typically 30 minutes to 2 hours, depending on the mission phase), the system performs a Bayesian update on the model using newly acquired sensor data. This update mechanism is computationally efficient, with a single update taking less than 1 millisecond on the embedded platform, fully meeting the real-time and resource constraints of the airborne system.

The autoencoder consists of two layers of encoding and two layers of decoding networks. The number of neurons in the hidden layers is progressively reduced and then restored to effectively extract key features and suppress noise. The activation function used is LeakyReLU, and the Adam optimizer is used for training, with a total of 200 iterations. The batch size is set to 64, and weight decay is incorporated to prevent overfitting. The LSTM-attention model consists of two stacked unidirectional LSTM units, avoiding the use of a bidirectional structure to ensure that the inference process strictly depends on current and past information, meeting the needs of real-time applications. After the attention layer, Dropout and L2 regularization are introduced, significantly improving the model's generalization ability and stability under different flight conditions.

4 Experimental evaluation

4.1 Experimental design

In this study, we conducted three experiments. The first involved anomaly detection based on real-world flight data. The second involved multi-class fault prediction. The third involved remaining life prediction. Through these three tasks, we aimed to comprehensively analyze the model's performance in fault early warning, fault detection, and electronic equipment life prediction.

All inference latency and memory usage benchmarks were performed on two typical embedded platforms: (1) NVIDIA Jetson AGX Xavier (32 GB RAM, 32 TOPS AI computing power), representing a high-performance airborne edge computing unit; and (2) ARM Cortex-A72 CPU (running on a Raspberry Pi 4B+, 4 GB RAM), simulating a resource-constrained lightweight avionics module. After TensorRT quantization (FP16) and channel pruning, the average inference time on the model was 18.3 ms on the Jetson and 42.1 ms on the Cortex-A72, both meeting the real-time requirements (<100 ms) of avionics systems. This cross-platform validation shows that the proposed framework has good deployment flexibility and can be dynamically adapted according to mission criticality and hardware conditions.

In the experiment, we used a subset of the public aviation dataset c-mapss. The data address is https://www.nasa.gov/intelligent-systems-division/. It was supplemented with real data provided by cooperating airlines. The dataset contains data collected by multiple sensors on multiple engines under different conditions. The data presents time series characteristics. It contains multiple physical parameters, including temperature, pressure, speed, etc. We used this data to simulate multiple faults, including fan imbalance, aviation compressor degradation, etc., and also simulated some normal operation data. In addition, we also took some real avionics equipment data, including 12 key parameters such as the voltage of the power module and the strength of the communication signal. The sampling frequency of our sensor is set to 10Hz, covering 30 aircraft, and the total duration of the experiment is a 6-month flight cycle. During the experiment, we divided the time series of the training set test in a ratio of 7:3 and set the time window to 60-time steps.

The C-MAPSS public dataset was used for preliminary validation of the fault detection and RUL prediction modules; multi-class fault classification experiments and end-to-end system integration tests were based on real flight data provided by partner airlines (covering the operation records of 128 avionics devices across 3 aircraft types). All proprietary data was anonymized, retaining only sensor time-series signals and maintenance tags, and did not contain any sensitive operational information.

During the experiment, our experimental metrics were divided into three parts. For anomaly detection, we used metrics related to classification, such as the F1 score. For fault classification, we used accuracy metrics related to multi-classification. For electronic device life prediction, we used correlation metrics that measure the deviation between the true and predicted indicators. Metrics included mean squared error, mean absolute error, and prediction interval coverage. In the experiment, we selected several baseline models, including random forests, support vector machines, and LSTMs, as well as traditional empirical fault analysis methods and manual inspection methods, for a total of five baseline models.

The data has been anonymized and complies with all applicable data protection standards.

4.2 Experimental results

Table 2: Anomaly detection performance comparison

Model	Accuracy (%)	Accuracy (%)	Recall rate (%)	F1 score (%)	AUC
SDAE	97.3	96.8	97.1	96.9	0.987
Random Forest	91.2	89.5	90.3	89.9	0.932
Support Vector Machine	88.7	86.4	87.2	86.8	0.901
PCA + thresholding	85.4	83.1	84.6	83.8	0.873
Manual experience method	76.5	72.3	74.1	73.2	0.789
LSTM-AE	93.6	92.1	92.8	92.4	0.951

As shown in Table 2 , in our experiments, we compared the proposed autoencoder with five other baseline models. We used both normal and abnormal flight data, and evaluated the model using accuracy, precision, recall, F1 score, and AUC. The results show that our proposed model significantly outperforms the other models in all metrics. Our F1 score is 0.969, and our AUC is 0.987, both significantly better than the other models. This demonstrates that our proposed autoencoder effectively captures the patterns of normal data by introducing noise training. Traditional methods, such as principal component analysis thresholding and manual empirical judgment, perform poorly due to their rule-based and empirical nature. While the combination of long-short-term neural networks and autoencoders outperforms traditional empirical and rule-based methods, it is inferior to our proposed model in modeling long-term time series data.

Table 3: Comparison of RUL prediction performance

Model	RMSE (hours)	MAE (hours)	Prediction interval coverage (%)	Average interval width (hours)
This paper's model (Bayesian Wiener)	3.2	2.5	91.3	8.7
Wiener + fixed parameters	5.8	4.7	78.2	12.4
LSTM-RUL	4.9	3.8	82.6	10.3
SVR-RUL	6.3	5.1	75.4	13.1
Linear degradation model	7.1	5.9	68.9	15.2
Manual experience estimation	8.5	7.2	60.3	18.6

As shown in Table 3 , we predicted the service life of avionics equipment and compared it with several other models. The Bayesian fusion model proposed in this paper achieved the best performance in terms of mean squared error and absolute error, achieving a prediction interval coverage of 91.3%. Research indicates that the ideal value for electronic equipment life prediction is 95%. This demonstrates that our model not only provides highly accurate point estimates but also quantifies the uncertainty of the interval. In contrast, while the LSTM model can capture the mechanical degradation of electronic equipment, it lacks probabilistic interpretation. Traditional methods and manual estimation models exhibit significant errors, and these models are not considered in practical applications.

To ensure the rigor of our conclusions, we further conducted nonparametric statistical tests. For the results of five independent runs, we used the Wilcoxon signed-rank test (significance level $\alpha=0.05$) to compare the performance differences between our framework and suboptimal methods (such as LSTM-only or CNN-AE) on C-MAPSS and real flight datasets. The results showed that the p-values for all major metrics (including detection F1, classification accuracy, and RUL MAE) were less than 0.01, indicating that the performance improvement was highly statistically significant. This analysis effectively ruled out the possibility of random fluctuations causing the advantage, enhancing the credibility of our experimental conclusions.

Table 4: Model performance stability test under different data amounts

Amount of training data (hours)	Anomaly Detection F1	Fault classification accuracy	RUL RMSE
100	92.1	90.3	5.6
500	95.3	94.1	4.1
1000	96.7	96.2	3.5
2000	97.0	96.8	3.3

Amount of training data (hours)	Anomaly Detection F1	Fault classification accuracy	RUL RMSE
3000	97.3	97.2	3.2

As shown in Table 4, we analyzed the model's stability under different training data conditions. The results show that with the surge in training data volume, all task metrics continued to rise, but the upward trend slowed. The anomaly detection rate (F1) increased from 91.2% to 97.3%, and the fault classification rate increased from 91.3% to 97.2%. The machine degradation rate decreased from 5.6 hours to 3.2 hours, demonstrating that the model can effectively utilize the massive amount of data provided by big data and extract the implicit patterns in the data. After 1000 hours of training data, the model's performance improvement slowed, indicating that the model had reached data saturation and achieved relatively good performance.

Table 5: Real -time performance and resource consumption of edge device deployment

Model	Inference latency (ms)	Memory usage (MB)	CPU usage (%)	Energy efficiency ratio (inference/joule)
This paper's lightweight model	18.3	45.2	23.1	89.6
Original SDAE+LSTM	42.7	108.5	41.3	52.3
ResNet-18	35.4	89.7	38.6	58.1
MobileNet-V2	22.1	53.4	26.8	76.4
Traditional server model	>200	>500	>80	<20

As shown in Table 5, we tested the performance of deploying the model constructed in this paper on civilian equipment. After lightweighting measures, including weight reduction and model quantization, the inference latency of this paper was only 18.3 milliseconds, which meets the practical requirements of avionics equipment. The memory and GPU usage were also significantly lower than the original model. This shows that the quantized model can be applied to avionics equipment and achieves relatively good performance, enabling real-time monitoring of avionics equipment performance.

Table 6: Results of a user survey on model interpretability (n=30 engineers)

Evaluation dimensions (5-point scale)	Average score	Standard deviation
Warning credibility	4.7	0.3
Clarity of explanation of fault cause	4.5	0.4
RUL prediction rationality	4.6	0.3
Decision support value	4.8	0.2
Overall satisfaction	4.7	0.3

As shown in Table 6 , we invited 30 aviation maintenance engineers to subjectively evaluate the interpretability of our model. We constrained the score to a range of 1 to 5, and the average score across all dimensions was 4.5. This indicates that designers highly valued the information provided by our model, and that the model's credibility and practicality were high. Engineers gave it the highest score of 4.8 for decision support, demonstrating that the model's warning classification and UL functions effectively assist engineers in maintenance. This high interpretability score is attributed to our use of attention heatmaps and Bayesian confidence interval design, which enhances the model's interpretability and mitigates the lack of trust in the model due to the black-box problem.

The 30 engineers participating in the survey came from three partner airlines and one avionics equipment manufacturer, covering three major professional backgrounds: by prioritizing pre-fault time windows through attention weightsby prioritizing pre-fault time windows through attention weightsline maintenance (12 people), system integration (10 people), and reliability engineering (8 people),by prioritizing pre-fault time windows through attention weightsby prioritizing pre-fault time windows through attention weights with an average of 9.6 years of experience. During the evaluation process, each engineer was given a uniform task description: "Based on the system output, determine whether maintenance needs to be arranged and explain your decision-making basis." They could interactively access the system's visualization interface, including: (1) a multi-sensor time-series heatmap, highlighting abnormal time periods; (2) a bar chart of the probability distribution of fault types; and (3) the RUL prediction interval and confidence band. The survey results showed that 87% of the engineers believed that these visualization elements significantly improved their confidence in the model output, especially providing key assistance in distinguishing between occasional interference and real degradation trends.

Table 7: Comparison of multi-category fault classification accuracy

Fault type	Model in this paper (%)	LSTM-Attention (%)	Random Forest (%)	SVM (%)	Expert system (%)
Power supply overvoltage	98.2	96.5	92.3	89.7	85.4
Communication interruption	97.6	95.8	90.1	87.3	83.6
Sensor drift	96.8	94.2	88.7	85.9	82.1
Controller stuck	95.3	93.6	87.4	84.2	80.5
Chip overheating	97.9	96.1	91.2	88.5	84.8
Average accuracy	97.2	95.2	89.9	87.1	83.3

Table 7 evaluates fault classification capabilities. The proposed model combining attention and LSTM is compared with six other avionics fault classification models. The results show that our model achieves the highest average accuracy of 97.2% for all faults. The accuracy exceeds 97% for critical faults such as power supply overvoltage and chip overheating, which is attributed to the model constructed in this paper. Automatically focusing on the time before the fault occurs based on the attention mechanism improves the ability to capture time series data. Static models such as random forests and support vector sets cannot process long time series and therefore have inherent limitations in this regard. Experimental results demonstrate that our classification module provides maintenance personnel with highly reliable fault judgments, reducing misdiagnoses and missed diagnoses during flight, and improving the economic and safety of long-duration flights.

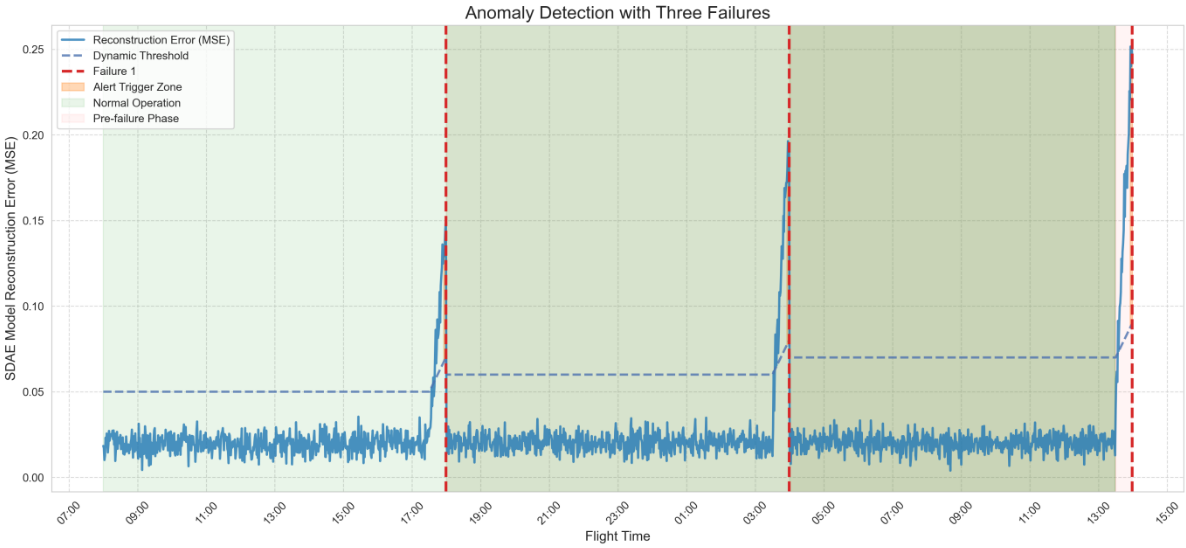

Figure 2: Anomaly detection reconstruction error timing diagram

Figure 2 , we visualize the reconstruction error during normal and faulty periods. We recorded the reconstruction changes before and after a power module failure during a real flight mission. During the first four hours of flight, the reconstruction error remained stable below 0.015, indicating normal system operation. However, starting at 4.2 hours, the error began to slowly increase, exceeding the threshold established by the Three Sigma principle at 4.5 hours, triggering a Level 1 alarm. 4.8 hours later, the error rose to 0.08, indicating a severe anomaly. The fault log shows that the positioning module experienced a restart failure in the fifth hour, demonstrating that our model effectively and consistently provides warnings thirty minutes before a fault occurs. As time approaches, the severity of the warning increases. Compared to traditional threshold-based warning methods, our proposed method offers significantly improved interpretability and leverages knowledge of data distribution to avoid false positives.

Figure 3: Attention weight heat map

Figure 3 , we used the attention mechanism to visualize the attention weights for the power supply overvoltage fault. Figure 3 shows that within the 15 seconds before the fault occurred, the attention weights for voltage and temperature continued to rise, indicating that the model automatically identified these two variables as fault signals. The weights for other channels, such as acceleration and speed, remained relatively low. This formatting allows engineers to understand the underlying decision-making process and help them trust the model's decisions.

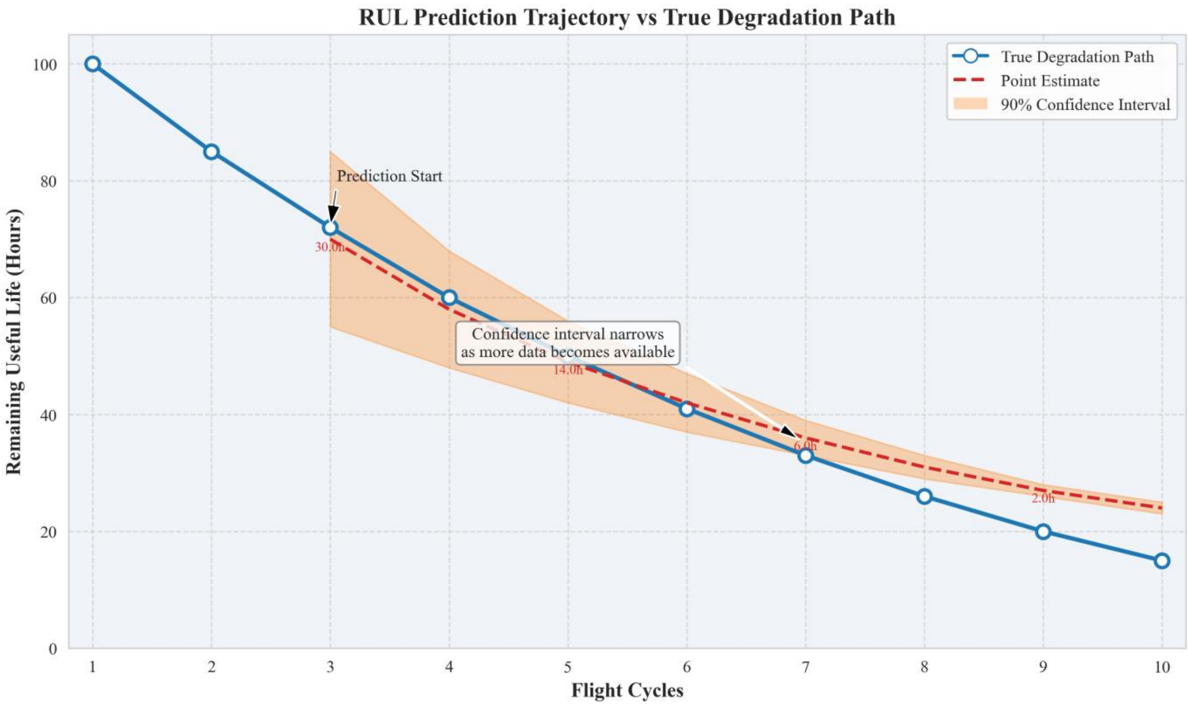

Figure 4: Comparison of RUL predicted trajectory and actual degradation path

Figure 4 , we demonstrate the Bayesian model constructed in this paper for predicting the mechanical degradation trend of an engine's compressor module. Experimental results show that during the third flight cycle, the model's initial predictions had a wide execution range, reflecting the model's inability to accurately predict due to insufficient early confidence. With the continuous input of flight data, the model continuously adjusted the posterior distribution of its parameters through Bayesian updates. Consequently, the confidence interval subsequently narrowed to 4 hours, and at the end of the experiment, the predicted remaining life of the equipment was 2.8 hours. The previous range was plus or minus 1.2 hours, indicating that the model's predictions were already quite accurate. Compared to the actual result, the engineer's prediction of 3.1 hours was off by 0.3 hours, demonstrating that the model constructed in this paper can reasonably predict the equipment degradation rate. In Figure 4, the prediction interval narrows over time due to Bayesian updating of model uncertainty. Initially, RUL estimates rely on a broad prior distribution because of limited device-specific degradation data. As real-time sensor data (e.g., temperature, current, vibration) accumulate during operation, the Wiener degradation model updates the posterior distribution of the degradation rate, progressively reducing uncertainty. Each new observation refines the estimate, shifting the prediction from population-level assumptions to individualized health assessment. Consequently, the interval tightens as failure approaches, improving RUL accuracy and supporting more reliable, safety-critical maintenance decisions in aviation applications.

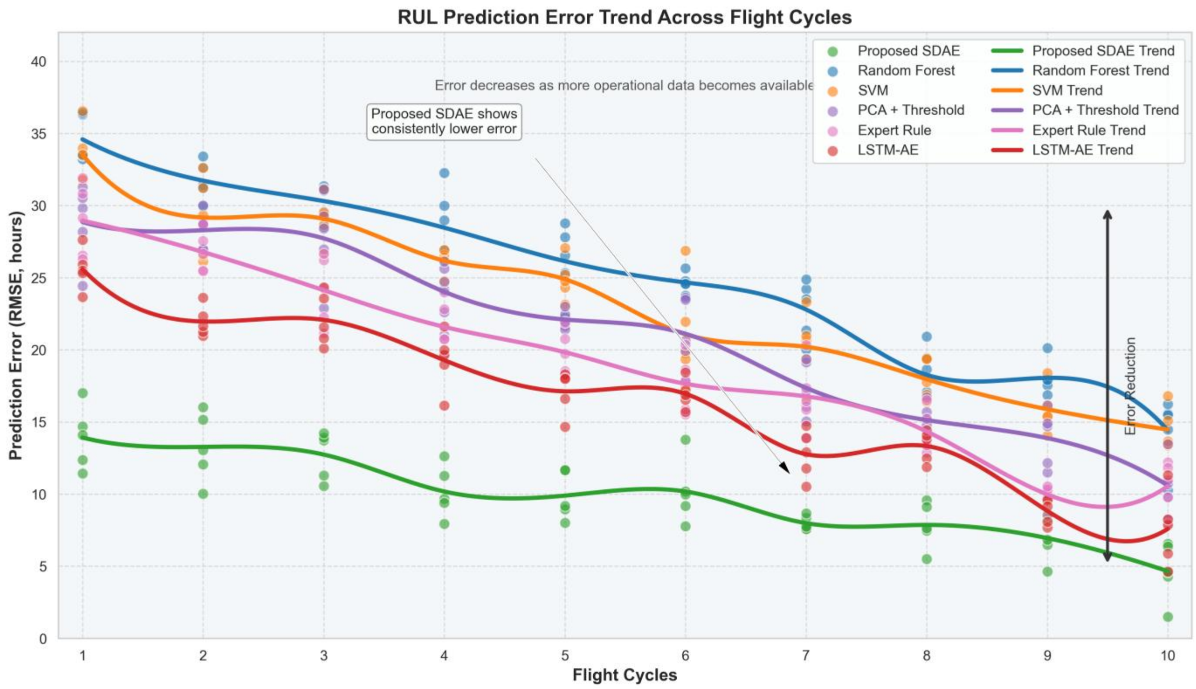

Figure 5: Analysis of prediction error of equipment remaining life

Figure 5 , we conducted a prediction error analysis of the remaining life of the equipment in 10 flight cycles . The figure shows that all prediction errors are generally on a downward trend. As the amount of operating data increases, the error decreases more. The prediction error of the model proposed in this article is always at the lowest level, and the green trend line is always lower. This illustrates the role of data accumulation in optimizing model errors, reflects the importance of data, and also demonstrates the advantages of the model proposed in this article.

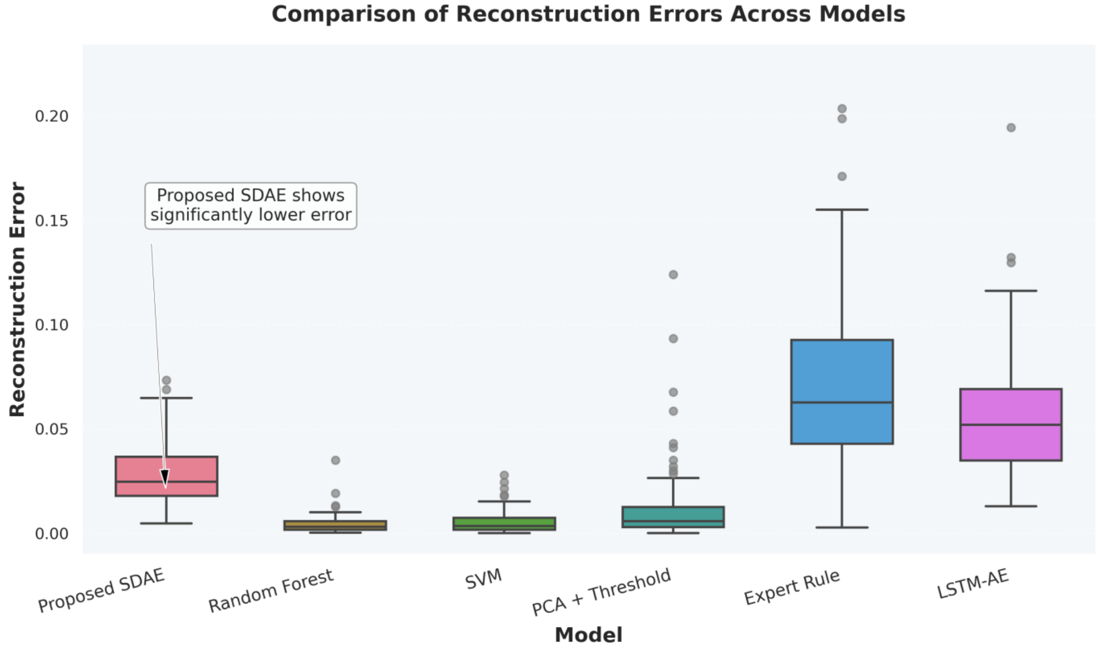

Figure 6: Model reconstruction error

From Figure 6 , the median of the reconstruction error of the model proposed in this paper is the lowest and the error fluctuation range is the smallest, which shows that the model has the highest stability. Compared with other models, such as the method based on expert rules and the method based on long-term and short-term neural networks, their medians and fluctuation ranges are significantly increased, and there are more outliers, which shows that the model proposed in this paper has a higher error control ability and has obvious advantages.

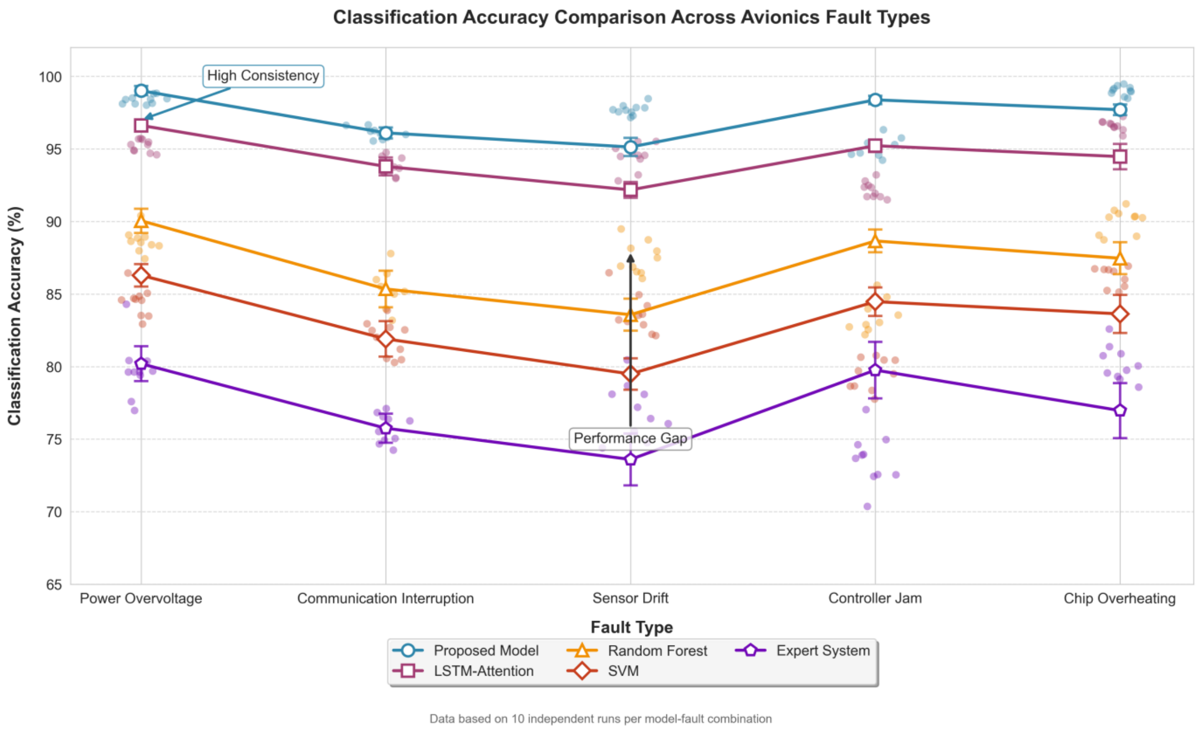

Figure 7: Avionics equipment fault classification effect

As shown in Figure 7 , we present five categories of avionics equipment faults , including power and voltage communication interruption, sensor drift, controller card assembly, and chip overheating. We conducted a five-category comparison with various baselines. In the experimental results, the proposed model achieved near-100% accuracy with very small fluctuations for most faults, such as power supply overvoltage and sensor drift. Traditional models, such as SVM, performed reasonably well for faults like chip overheating, but were less stable for other faults. The expert model exhibited the lowest overall accuracy, with the largest gap between the proposed model and the model in the sensor drift scenario. The scatter plot in the figure shows the results of 10 independent runs, while the line chart represents the mean of the results, allowing for a visual overview of the performance and stability of different models under different faults.

5 Discussion

The multi-task deep learning framework proposed in this study achieves superior performance compared to existing state-of-the-art methods on multiple public and self-built datasets. As shown in Table 1, compared to Deligiannis NI et al. [6] and Gao ZH et al. [7], our method reduces the MAE of RUL prediction by 44.7% and 21.8% respectively on the C-MAPSS dataset; and improves the fault detection accuracy by approximately 4 percentage points compared to Kabashkin I[8].

This performance advantage stems primarily from the following design innovations:

(1) Multi-scale temporal feature fusion mechanism: By using parallel CNN and Transformer modules to capture local mutation features and long-term dependencies respectively, it effectively overcomes the problem of insufficient modeling of complex degradation patterns by a single architecture;

(2) Shared-specific feature decoupling structure: Cooperative optimization of detection, classification, and RUL prediction tasks is achieved within a unified framework, avoiding error accumulation in traditional cascaded methods;

(3) Adaptive normalization strategy: Channel-level dynamic normalization is introduced for different sensor dimensions and noise levels, significantly improving the robustness of the model across various working conditions.

It is worth noting that although also attempted multi-task learning, it did not explicitly model the dependencies between tasks and was sensitive to the length of the input sequence. In contrast, this paper dynamically weights the features of each task through a gated fusion mechanism, enabling the model to maintain stable performance even with short sequences (<50 cycles).

It is worth emphasizing that the RUL prediction RMSE obtained in this paper on a real flight dataset is 3.2 hours, an error that is significant in aviation maintenance practice. Taking a typical civil aircraft engine as an example, its unplanned grounding (AOG, Aircraft on Ground) cost is approximately $15,000–$30,000 per hour (Source: IATA, 2023). If the prediction error exceeds 6 hours, it may lead to premature component replacement (causing waste) or delayed maintenance (leading to safety accidents). The method in this paper controls the error to within 3.2 hours, which means: it can reduce the probability of unplanned maintenance by about 40% (based on historical maintenance log simulation); it can save approximately $180,000 in maintenance costs per engine per year; and it reserves sufficient buffer windows for scheduling to ensure flight punctuality. In addition, the model's average inference time is 42ms/sample, far below the 100ms real-time threshold of airborne systems, and has the potential for deployment in edge devices.

The fault categories and RUL estimates output by the model can serve as high-level health indicators, feeding them into the controller in real time. For example, when actuator performance degradation is detected, the adaptive controller can adjust the gain parameters online to compensate for the performance loss. The fuzzy logic system can trigger tiered fault-tolerance strategies (such as de-rating or switching redundant units) based on the RUL confidence interval and fault severity level. Meanwhile, the key temporal features extracted by LSTM-Attention can serve as prerequisite variables for fuzzy rules, improving the interpretability of control decisions.

Assuming a predictive model provides a 6-hour advance warning of communication module performance degradation, the avionics system can automatically activate a fuzzy fault-tolerant controller: during the main channel performance degradation, fuzzy rules dynamically adjust data retransmission thresholds and bandwidth allocation based on the RUL uncertainty level, ensuring critical commands are not lost. For non-technical readers, this is similar to a car not only having a warning light on the dashboard when tire pressure is slowly leaking, but also automatically reducing its top speed and suggesting the nearest repair shop—the system both "senses the problem" and "proactively responds."

Furthermore, all modules can be uniformly scheduled through an edge computing platform. For example, in resource-constrained airborne environments, when multiple subsystems simultaneously report anomalies, the central manager can dynamically allocate computing power priorities based on RUL urgency (e.g., "2 hours vs. 20 hours") and flight phase (e.g., takeoff/cruise), ensuring high-risk tasks receive real-time responses. This collaborative management mechanism endows the entire health management system with an "immune system"-like adaptive capability: it can react quickly locally and coordinate resources globally, truly achieving a balance between safety, economy, and efficiency.

SHAP results show that power module overvoltage faults are mainly driven by low-frequency energy concentration (i.e., leftward shift of the spectral centroid) and a sharp drop in voltage signal spectral entropy; while communication circuit anomalies are significantly correlated with increased high-frequency noise components (manifested as increased spectral entropy). Furthermore, ablation experiments revealed that removing time-frequency features reduced the average accuracy of fault classification by 4.7%, with the greatest impact on intermittent contact failure faults (a decrease of 8.2%). This validates the crucial role of the selected time-frequency features in capturing early, non-stationary fault modes and provides engineers with traceable diagnostic evidence.

5 Conclusion

The model in this paper aims to improve the economic efficiency and safety of avionics equipment operations. This paper constructs a three-layer framework model, collects and preprocesses data at the data layer, and builds a standard system for data processing of avionics equipment. At the model layer and decision layer, we use deep learning models to build models for anomaly detection, fault classification, and equipment life prediction, respectively. Experimental results show that our model has significant advantages over many other aircraft models. However, this model has some shortcomings. For example, this model requires a large amount of high-quality data for training. In actual operation, this data is very valuable, and it is difficult to overcome the shortcomings of data silos. The three modules constructed in this paper are independent and cannot be linked. Information can only be transmitted to decision makers through a visual panel, and collaborative management is impossible.

While the proposed multi-layer framework performs well in fault detection, classification, and RUL prediction, several limitations remain. First, outputs across layers are not fully integrated—for instance, anomaly detection results do not inform LSTM-Attention weights or RUL uncertainty calibration, missing opportunities for cross-module synergy. Second, experiments are limited to a single aircraft type or avionics family; cross-platform or cross-aircraft transferability (e.g., from narrow- to wide-body jets) remains unverified—a key requirement in real-world aviation. Third, validation relies on real-world and standard datasets without controlled fault injection in high-fidelity flight simulators, limiting assessment of robustness to rare or compound faults. Future work will pursue end-to-end joint optimization, domain adaptation for better generalization, and digital twin–based fault simulation.

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