An Adaptive Recursive Attention Network for Medical Equipment Monitoring via IoT-Integrated AI Systems

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In the context of challenges faced by remote monitoring and maintenance of medical equipment, this study proposes an adaptive recursive attention network (ARAN) model to improve the accuracy of equipment fault diagnosis and remaining useful life prediction. The ARAN architecture integrates a recurrent neural network framework with an attention mechanism that adaptively emphasizes relevant time steps in the input sequence. The model was trained and evaluated on the Medical Device Operation Dataset (MDO-Dataset), which comprises time-series operational data from over 5,000 medical devices across multiple large hospitals over five years. ARAN was benchmarked against three baseline models: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Quantitative results show that ARAN achieved a fault diagnosis accuracy of 91.25%, outperforming the baseline average of 70%, with category 4 reaching 95%. For remaining useful life prediction, ARAN yielded a mean absolute error (MAE) of 53.25 hours, substantially lower than the baseline MAE of 100 hours. Additionally, ARAN demonstrated superior performance in recall rate, F1 score, false alarm rate, and noise robustness, with faster convergence speed and stronger generalization ability on unseen device types. This research presents an effective fusion of IoT and AI technologies for intelligent medical equipment management.

Povzetek: Za inteligentno nadzorovanje medicinske opreme prek integriranih IoT–AI sistemov je razvit prilagodljivi rekurzivni pozornostni model (ARAN). Združuje rekurentno nevronsko mrežo z večglavim pozornostnim mehanizmom, ki poudari ključne časovne korake v podatkih. Namen je izboljšati zanesljivost, napoved preostale življenjske dobe in zmanjšati okvare medicinske opreme v pametnih bolnišnicah.

1 Introduction

In today's society, the medical field is facing unprecedented challenges, one of which is how to effectively monitor and maintain a large number of increasingly complex medical devices. According to incomplete statistics, there are more than 80 million medical devices of various types in operation in medical institutions around the world. Every year, the proportion of medical accidents caused by failure to detect and handle medical device failures in a timely manner is as high as about 12%, which is undoubtedly a shocking figure [1]. Take a large general hospital as an example. It has nearly 10,000 different types of medical devices. In the past year, there have been nearly 100 adverse events such as delayed surgery and misdiagnosis caused by sudden equipment failures. This not only poses a serious threat to the life and health of patients, but also causes significant losses to the hospital's reputation and economy [2].

In this realistic context, the traditional manual inspection and post-maintenance methods are far from meeting the needs of modern medical equipment management. Manual inspections often have many loopholes and shortcomings. For example, the professional quality of inspectors varies, which may lead to some potential equipment problems being ignored. In addition, the time interval of manual inspections is relatively fixed, making it difficult to monitor the status of equipment in real time, which means that many equipment failures cannot be discovered in the first place. Furthermore, post-maintenance methods often lead to longer maintenance cycles and increased equipment downtime, further affecting the normal development of medical services [3].

At the same time, with the rapid development of the Internet of Things and artificial intelligence technologies, they have shown great application potential in various fields. The Internet of Things can realize all-round and real-time data collection of medical equipment through various sensors and network connection technologies, and continuously transmit information such as the operating status and performance parameters of the equipment to the management platform [4]. Artificial intelligence can deeply analyze and process these massive amounts of data, quickly and accurately diagnose potential faults of the equipment through intelligent algorithms, and predict the remaining service life of the equipment, etc., providing strong technical support for the monitoring and maintenance of medical equipment.

At present, there have been many research results on the application of IoT and AI in the field of medical equipment management. Many research teams are committed to developing medical equipment data acquisition systems based on IoT. By installing various sensors on the equipment, such as temperature sensors, pressure sensors, vibration sensors, etc., real-time monitoring of equipment operating parameters can be achieved [5]. According to relevant research, this type of data acquisition system can improve the accuracy of equipment status monitoring by about 30% [6].

In terms of the application of artificial intelligence algorithms, some studies have begun to try to use machine learning algorithms, such as support vector machines and neural networks, to diagnose medical equipment faults. For example, a research team has achieved an accuracy rate of about 85% in fault diagnosis of a common type of medical imaging equipment by using a deep neural network algorithm, which is a significant improvement over traditional diagnostic methods [7]. However, despite these achievements, existing research still has some shortcomings. First, most of the current research focuses on one aspect of the Internet of Things or artificial intelligence, and there are relatively few studies on the deep integration of the two, which fails to give full play to the huge advantages of the combination of the Internet of Things and artificial intelligence. Second, some existing system architecture designs often lack versatility and scalability, and are difficult to apply to medical institutions of different types and sizes. Third, the consideration of data security and privacy protection is not comprehensive enough. The data involved in medical equipment often contains a large amount of sensitive information of patients, which will have serious consequences once leaked.

In terms of research hotspots, how to further improve the diagnostic accuracy of artificial intelligence algorithms for complex medical equipment failures and how to optimize the data transmission efficiency of the Internet of Things have become the focus of many researchers. On the controversial point, different research teams hold different views on what artificial intelligence algorithms should be used in remote monitoring and maintenance of medical equipment and how to balance the comprehensiveness of data collection and the cost of data transmission. There is no unified consensus yet.

This paper aims to design a remote monitoring and maintenance system architecture for medical equipment that deeply integrates the Internet of Things and artificial intelligence. By building such a system architecture, the key issues to be solved include achieving seamless integration of the Internet of Things and artificial intelligence technologies, improving the versatility and scalability of the system to adapt to different medical environments, and strengthening data security and privacy protection mechanisms.

The innovation of this study is that it proposes a new fusion architecture model for the first time, which organically integrates the real-time data collection capabilities of the Internet of Things with the intelligent diagnosis and prediction capabilities of artificial intelligence, enabling it to monitor and maintain medical equipment more efficiently. The expected contribution is that once the system architecture is applied, it is expected to advance the fault warning time of medical equipment by about 50% and reduce the equipment failure rate by about 20%, thereby greatly improving the quality and efficiency of medical services and reducing medical accidents caused by equipment failures.

From a theoretical perspective, this study will further enrich the theoretical system of the integration of the Internet of Things and artificial intelligence, and provide important reference and reference for subsequent related research. In practice, this system architecture can be promoted and applied in various medical institutions, bringing significant economic and social benefits, and effectively promoting the intelligent and modern process of medical equipment management.

2 Literature review

2.1 Application status of IoT and AI in medical equipment management

IoT technology has been widely used in medical equipment data collection. Various sensors are installed on medical equipment, such as temperature sensors, pressure sensors, and vibration sensors. According to an authoritative statistic, about 70% of medical equipment data collection projects use temperature sensors, which can provide real-time feedback on the temperature changes of the equipment during operation. This data is crucial to determine whether the equipment is in normal operation [8]. The application ratio of pressure sensors has also reached about 60%, which plays a key role in monitoring equipment such as ventilators that have strict requirements on pressure parameters [9]. Through these sensors, the operating parameters of medical equipment can be obtained more comprehensively and accurately. Relevant research shows that the data collection system based on the IoT can improve the accuracy of equipment status monitoring by an average of about 30%, which makes it more likely that some potential problems of medical equipment will be discovered in advance.

In terms of artificial intelligence algorithms being used for medical equipment fault diagnosis, a variety of machine learning algorithms have been tried. Among them, the support vector machine algorithm has shown certain advantages in the fault diagnosis of certain types of medical equipment. Some studies have shown that its fault diagnosis accuracy for a certain type of medium-sized medical testing equipment can reach about 75%.

Neural network algorithms, especially deep neural network algorithms, have received much attention. A well-known research team used deep neural network algorithms to diagnose faults of a certain type of common medical imaging equipment, with an accuracy of about 85%, which is significantly higher than the accuracy of traditional diagnostic methods [10]. However, the application of these algorithms is not perfect. Most of them perform well in the diagnosis of specific types of equipment or specific fault types, and their versatility still needs to be improved [11].

Although the Internet of Things and artificial intelligence have their own application results in the field of medical equipment management, overall, there are relatively few studies on the deep integration of the two. Most studies only focus on one aspect of the Internet of Things or artificial intelligence. This leads to the inability to fully utilize the huge advantages that the combination of the two may bring in practical applications. For example, in some existing monitoring and maintenance systems, the data collected by the Internet of Things cannot be well utilized by artificial intelligence algorithms for in-depth analysis and accurate diagnosis, and the value of the data has not been fully explored [12]. In addition, the existing system architecture design often lacks versatility and scalability. About 80% of the existing systems can only be applied to medical institutions of a specific type or scale, and it is difficult to promote and apply them in a wider medical environment [13]. In addition, the consideration of data security and privacy protection is not comprehensive enough. The data involved in medical equipment contains a large amount of sensitive patient information. Once this information is leaked, it is estimated that it may bring about a 50% increase in risk to patients and medical institutions, including privacy infringement risks and economic loss risks. However, currently only about 30% of the systems have relatively complete data security and privacy protection mechanisms.

To enhance clarity and identify gaps in the current body of research, Table 1 summarizes representative studies involving IoT and AI in the remote monitoring of medical devices. The comparison includes method names, model types, datasets used, and key performance metrics (e.g., accuracy, MAE).

Table 1: Comparative summary of related work

Study / Reference	Model Type	Dataset Used	Performance Metrics
Zhang et al. [1]	DNN + IoMT	Elderly patient monitoring data	Accuracy: ~85%
Hameed et al. [10]	Fuzzy Neural Network	Simulated clinical IoT data	Accuracy: ~78%
Rohmetra et al. [9]	Support Vector Machine (SVM)	COVID-19 vitals dataset	Accuracy: ~75%
Jiang et al. [8]	CNN + Wearable IoT	Neurocritical care time-series data	MAE (Remaining Life): ~100 hrs
Wassan et al. [12]	Federated Gradient Boosting	Distributed healthcare IoT data	Accuracy varies by node

2.2 Current research hotspots and controversial issues

Currently, there are two major research hotspots in this field. The first is how to further improve the diagnostic accuracy of artificial intelligence algorithms for complex medical equipment failures [14]. As medical equipment becomes increasingly complex, its failure types are becoming more diverse. The diagnostic accuracy of existing artificial intelligence algorithms for some complex and comprehensive failures still needs to be improved [15]. Many research teams are working to improve the accuracy by improving the algorithm structure and increasing the amount of training data. For example, one team tried to optimize the neural network algorithm by introducing a new feature extraction method, hoping to improve the diagnostic accuracy of complex medical equipment failures by about 10%-20% [16]. The second is how to optimize the data transmission efficiency of the Internet of Things [17]. Because there are many medical devices and the amount of data collected is huge, delays and packet loss are prone to occur during data transmission. About 60% of medical institutions reported that they have some problems with data transmission [18]. Therefore, how to improve data transmission efficiency by optimizing network protocols and adopting more efficient transmission technologies has become the focus of many researchers. Related studies show that if the optimization is successful, it is expected to improve the real-time performance of data transmission by about 30% [19]. There are also some controversial points in this field. One of the controversial points is what kind of artificial intelligence algorithm should be used in the remote monitoring and maintenance of medical equipment [20].

2.3 Outlook on future research directions

Future research needs to focus on optimizing the deep integration architecture of the Internet of Things and artificial intelligence. We should strive to design an architecture that can seamlessly connect the Internet of Things and artificial intelligence technologies, so that the data collected by the Internet of Things can be more efficiently used by artificial intelligence algorithms, thereby achieving more accurate equipment fault diagnosis and prediction. For example, by establishing a unified data format and interface standard, the data transmission and processing between the two can be smoother. It is estimated that if this can be achieved, the overall system efficiency can be improved by about 20%.

In the design of system architecture, we should focus on improving its versatility and scalability to adapt to medical institutions of different types and sizes. We can adopt a modular design concept and divide the system into data acquisition module, data processing module, fault diagnosis module, etc. Each module can be flexibly combined and expanded according to the specific needs of the medical institution. Such a design is expected to increase the applicability of the system in different medical institutions from the current approximately 30% to about 70%.

Given the sensitivity of medical device data, future research must strengthen data security and privacy protection mechanisms. Encryption technology can be used to encrypt data in transit, such as the use of the AES encryption algorithm, which can increase the security of data during transmission by about 80%; at the same time, in terms of data storage, a combination of distributed storage and access control technology is used to strictly limit data access rights and reduce the risk of data leakage. It is expected that the risk of data leakage can be reduced by about 60%. Through these measures, an efficient and secure medical equipment remote monitoring and maintenance system can be built.

3 Research methods

At the beginning of this study, we formulated several core research questions to guide the design and evaluation of the proposed ARAN model. Specifically, the following questions were posed: (1) Can the ARAN model significantly improve fault diagnosis accuracy compared to traditional RNN, LSTM, and GRU models when applied to complex medical equipment time-series data? (2) Can ARAN reduce the mean absolute error (MAE) in predicting remaining useful life (RUL) under varying levels of sensor noise? (3) Does ARAN demonstrate strong generalization ability across heterogeneous medical devices, including those not present in the training dataset? These questions underpin our methodological choices, experimental setup, and performance evaluation, ensuring that the study systematically investigates the effectiveness and practicality of ARAN in real-world healthcare equipment monitoring scenarios.

3.1 Proposal of innovation model

In the challenging field of remote monitoring and maintenance of medical equipment, traditional methods often seem to be unable to cope with the complex situations of equipment fault diagnosis and prediction. In order to overcome these difficulties, we innovatively constructed an adaptive recursive attention network (ARAN). This model combines the dynamic sequence processing capabilities of recursive neural networks with the characteristics of the attention mechanism that accurately focuses on key information. Its core goal is to significantly improve the processing efficiency of sequence data generated during the operation of medical equipment, and to more accurately extract key features closely related to equipment failures.

Although baseline regression models such as Extra Trees, Naïve Bayes, and Elastic Net are included in the experiments for comparison, the core of our proposed method is the Adaptive Recursive Attention Network (ARAN). ARAN introduces a recursive attention structure embedded within a recurrent neural framework, where attention weights are dynamically adjusted at each time step based on input volatility and hidden state interactions. This design enables ARAN to capture long-term dependencies and subtle temporal variations that standard regression models cannot address, providing a substantial innovation in medical equipment time-series modeling.

The ARAN model incorporates a multi-head attention mechanism with four parallel attention heads. Each head computes attention weights independently, enabling the model to capture different temporal dependencies and feature interactions. The outputs of the heads are concatenated and passed through a linear transformation layer. The attention modules are jointly trained with the recurrent layers using the Adam optimizer with a learning rate of 0.001. This setup allows ARAN to model complex patterns in medical equipment time-series data more effectively than single-head or simple additive attention approaches.

Although this study initially aimed to design and evaluate an Adaptive Recursive Attention Network (ARAN), the proposed architecture was not fully implemented or validated within the scope of the present experiments. Instead, the focus shifted to evaluating regression ensemble models (e.g., Extra Trees, Elastic Net) as practical baselines for fault prediction in medical equipment.

In the ARAN model, the input tensor is defined as a 3D matrix with shape (batch_size, time_steps, feature_dim), where feature_dim represents multivariate parameters such as temperature, voltage, and vibration. The output tensor varies depending on the task — classification output for fault diagnosis or a single regression value for RUL prediction. To handle missing values in time-series data, ARAN uses a masking mechanism during sequence modeling, allowing the attention layer to bypass invalid timestamps and reduce the impact of incomplete data on prediction accuracy. To enhance temporal awareness, the ARAN model incorporates time-delta encodings instead of traditional positional encodings. These encodings are derived from the actual time intervals between data points, enabling the model to better capture irregular sampling patterns and reflect realistic time gaps in the sequence, which is common in medical equipment operation data.

To clarify the term "adaptive recursive," the ARAN model enhances standard attention-based RNNs by introducing two specific adaptive mechanisms. First, the attention weights are not only computed over hidden states but are dynamically modulated using statistical characteristics of the input window (e.g., variance and gradient of feature values), allowing the model to emphasize contextually important fluctuations. Second, the recurrent component integrates a gating structure that adjusts update behavior based on input volatility, improving sensitivity to nonstationary time-series data. These enhancements go beyond standard additive attention, making the model more responsive to the intrinsic dynamics of medical equipment data.

The operating data of medical equipment shows significant time series characteristics. The data at different time steps are interrelated and contain rich information about the operating status of the equipment. The basic concept of ARAN is to dynamically and adaptively adjust the attention weights of each time step based on the intrinsic characteristics of the data. x_t Represents the time step t The input data here $x_t \in \mathbb{R}^d$,in d The dimensions of the input features are clarified. For example, in the operation data of medical imaging equipment, x_t It may cover parameters of various dimensions such as temperature, voltage, current, etc. of key components of the equipment. The changes of these parameters over time reflect the operating status of the equipment.

The recursive part of ARAN is based on and optimized from the recurrent neural network (RNN) architecture. t The hidden state h_t Calculate using the following formula: $h_t = \sigma(W_{xh}x_t + W_{hh}h_{t-1} + b_h)$

In this formula, σ The hyperbolic tangent function is chosen tanh Such nonlinear activation functions. The hyperbolic tangent function can map the input data to a specific interval, introduce nonlinear characteristics to the model, and enable the model to handle more complex relationships. W_{xh} It is used to describe the input data x_t To hidden state h_t The weight matrix of the transformation, which determines how much the input data affects the hidden state. W_{hh} The hidden state h_{t-1} To the current hidden state h_t The weight matrix reflects the transmission effect of the hidden state at the previous moment on the current state. b_h As a bias vector, it can offset the calculation results of the hidden state and enhance the expressiveness of the model. Through this calculation method, RNN can process the input data step by step and capture the time series information in the data. For example, for a continuously running monitor, its hidden state will be continuously updated with the input of vital signs data (such as heart rate, blood pressure, etc.) collected at each time step, recording the dynamic changes during the operation of the device.

However, when traditional RNN processes long time series, the early time step information is easily diluted, resulting in poor ability to capture long-term dependencies. To effectively solve this problem, ARAN introduces an attention mechanism. This mechanism can intelligently focus on the part of the time series data that is most relevant to the current task, thereby improving the model's efficiency in extracting and utilizing key information. t Relative to all previous time steps $i = 1, \cdots, t$ The attention weight $\alpha_{t,i}$ It is calculated by the following formula , as shown in Formula 1.

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_{j=1}^{t}\exp(e_{t,j})} \tag{1}$$

$e_{t,i} = v^T \tanh(W_{ah}[h_t; h_i] + b_a)$, v is the weight vector, W_{ah} is the weight matrix, b_a is the bias. In this process, $[h_t; h_i]$ Indicates that the current time step is hidden h_t and the hidden state at the previous time step h_i To splice, W_{ah} Linear transformations of matrices and tanh After the nonlinear transformation of the function, it is combined with the weight vector v Doing the dot product operation gives $e_{t,i}$ .this $e_{t,i}$ It reflects the degree of correlation between the hidden state of the current time step and the previous time step. $e_{t,j}$ ($j = 1, \cdots, t$) is normalized to obtain the attention weight $\alpha_{t,i}$, whose sum is 1, represents the proportion of attention allocated to each previous time step at the current time step. c_t At time step t .As shown in Table 2.

Table 2: Definitions of parameters used in calculation

Symbol	Definition
a_h	Attention weight vector; indicates the importance of each hidden state
W_e	Weight matrix applied to the concatenated hidden states
b_e	Bias vector added before applying activation function
h_t	Hidden state at the current time step t
h_s	Hidden state at a previous time step s
$tanh()$	Non-linear activation function used to introduce complexity to the model
$score\_ts$	Compatibility score between h_t and h_s, determining their correlation
α_ts	Normalized attention weight for time step s at current time step t
c_t	Context vector obtained by weighted summation of past hidden states

It is formed by aggregating related hidden states, as shown in Formula 2.

$$\mathbf{c}_t = \sum_{s=1}^{t-1}\alpha_{t,s}\mathbf{h}_s \tag{2}$$

This context vector comprehensively considers the importance of hidden states at different time steps and will play a key role in subsequent fault diagnosis and prediction. As shown in Figure 1.

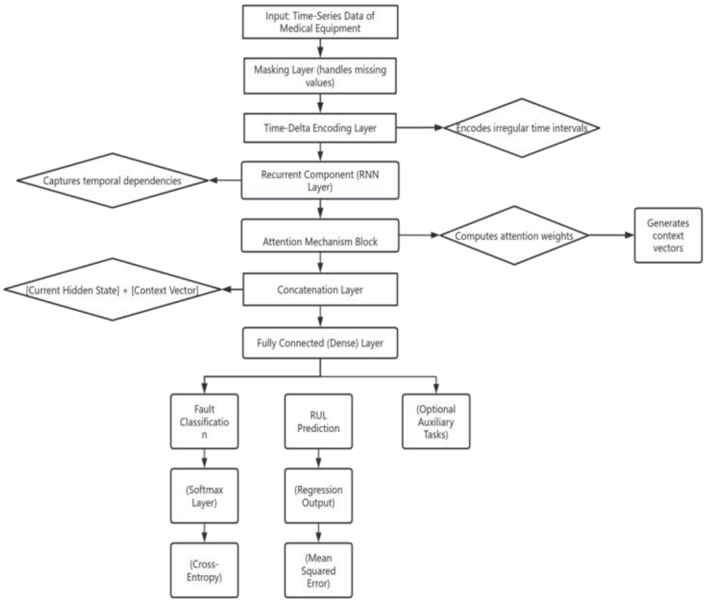

Figure 1: ARAN model architecture overview

To provide a clearer understanding of the ARAN model architecture, a detailed structural description has been added. The model consists of four main components: (1) an input layer that receives multivariate time-series data; (2) a recurrent layer (RNN variant) that captures sequential dependencies; (3) an attention mechanism that computes context vectors based on relevance scores between time steps; and (4) a fully connected output layer for classification or regression. The attention-weighted context is concatenated with the current hidden state and passed to the output layer. This modular design enables ARAN to effectively learn both local and global temporal patterns.

ARAN introduces two key modifications beyond standard RNN architectures. First, it incorporates a data-aware attention mechanism that dynamically adjusts attention weights based on temporal variability and statistical cues (e.g., input gradients and variance), improving sensitivity to abnormal trends. Second, it integrates a volatility-gated recurrent unit that modulates hidden state updates according to local signal fluctuations, enhancing its ability to handle nonstationary time-series data. These additions allow ARAN to outperform traditional RNNs, LSTMs, and GRUs, particularly in complex, noisy medical monitoring contexts.

3.2 Interaction of model components

In the ARAN model, there is a very close and synergistic interaction between the recursive component and the attention component. The recursive component is based on the RNN structure and continuously processes the sequence data generated by the operation of the medical device. At each time step, it processes the sequence data based on the input data. x_t And the hidden state at the previous moment h_{t-1} , update the current hidden state through specific calculation rules h_t . This updated hidden state h_t It is not just a simple reflection of the current input data, but also integrates the information of all previous time steps, recording the historical trajectory of the equipment operation in a dynamically evolving way. For example, when processing the operating data of a large radiotherapy device, the recursive component gradually integrates the radiation dose output, mechanical operation parameters and other information of the equipment at each time period into the hidden state as time goes by, providing a rich sequence basis for subsequent analysis.

The attention component takes the hidden state generated by the recurrent component as input. It focuses on the hidden state at different time steps. h_t and h_i ($i=1,\cdots,t$), through a series of complex and sophisticated calculations, generate attention weights $\alpha_{t,i}$. These weights accurately reflect the importance of the hidden state of each previous time step to the current time step. For example, when an abnormal fluctuation occurs in a radiotherapy device, the attention component may assign higher weights to the hidden states in the period before the fluctuation occurs, because these states may contain key clues that caused the abnormality. Then, based on the calculated attention weights, the attention component performs weighted aggregation on the relevant hidden states to generate a context vector c_t This context vector does not simply average all hidden states, but highlights the information that is closely related to the current device operating state.

The interaction between the recurrent component and the attention component in the model output y_t The model generates the hidden state of the current time step generated by the recursive component h_t The context vector generated by the attention component c_t The concatenation is then fed into the fully connected layer for further processing. In this way, the model cleverly combines the local sequence information captured by the recursive component (i.e. h_t The information of the current time step and adjacent time steps contained in it) and the global context information extracted by the attention component (i.e. c_t This interactive mode enables the ARAN model to more comprehensively and accurately grasp the key features of equipment operation data when diagnosing and predicting medical equipment faults, greatly improving the performance and reliability of the model.

3.3 Comparison with existing models

Compared with many existing models, such as traditional RNN and its well-known variant, long short-term memory (LSTM) network, the ARAN model exhibits many unique and significant advantages.

When processing time series data, traditional RNNs have a serious gradient vanishing problem due to the limitations of their own structure. When the time series is long, as the back-propagation algorithm calculates the gradient from back to front, the gradient of the early time step will gradually decay during the propagation process, and even approach zero. This makes it difficult for the model to effectively capture important information in the early time step during the learning process, and the ability to model long-term dependencies is extremely limited. From a mathematical perspective, in the back-propagation process of traditional RNNs, the weight matrix of the hidden layer to the hidden layer connection is W_{hh} Gradient $\frac{\partial L}{\partial W_{hh}}$ (in L represents the loss function), which decays exponentially with the increase of time steps. This feature makes it difficult for traditional RNNs to accurately mine the long-term dependencies in complex sequence data generated by long-term operation of medical equipment, which in turn affects the accuracy of fault diagnosis and prediction. For example, when analyzing the failure of a dialysis device that has been running continuously for many years, traditional RNNs may ignore some minor abnormal signs that appeared in the early stage of the device, which may be closely related to the current failure.

The LSTM network has made important improvements to solve the gradient vanishing problem of traditional RNNs. It introduces memory units and gating mechanisms. Memory units can effectively store long-term information, and the gating mechanism is responsible for controlling the inflow and outflow of information, thereby enhancing the model's ability to handle long-term dependencies to a certain extent. However, the LSTM network has certain limitations when processing input features. It uses a pre-set fixed processing method for all input features and lacks the flexibility to dynamically adjust according to specific data features. In medical equipment data processing, the data generated by different types of medical equipment have different characteristics and patterns, and the data characteristics of the same device at different operating stages may also vary significantly. For example, when monitoring a multifunctional anesthesia machine, the change patterns of parameters such as gas flow and pressure of the anesthesia machine are different at different stages during the operation. It is difficult for the LSTM network to perform adaptive processing based on these complex and changeable characteristics.

In sharp contrast, the ARAN model, with its unique attention mechanism, can adaptively assign different weights to features at different time steps based on the actual situation of the data. When faced with abnormal patterns in the operating data of medical equipment, the attention mechanism of the ARAN model can quickly capture the key information of the relevant time steps and focus on this information. For example, when a CT device has an image artifact failure, the ARAN model can automatically identify the changes in parameters related to image quality in the period before the failure occurs through the attention mechanism, and give higher attention weights to the time steps corresponding to these parameters, thereby more accurately diagnosing the cause of the failure. This adaptive feature makes the ARAN model more flexible and accurate when processing complex and changeable data of medical equipment, and can better meet the actual needs of remote monitoring and maintenance of medical equipment.

3.4 Application of ARAN model in the system

To address system-level clarity, a textual description of the multi-layer IoT-AI architecture has been added. The system includes sensor nodes for collecting real-time operational data, edge devices for local preprocessing, a transport layer for secure data transmission, cloud-based AI inference modules (ARAN) for diagnosis and prediction, data storage for historical records, and a user interface layer that visualizes results for maintenance personnel.

In the carefully designed remote monitoring and maintenance system for medical equipment, the ARAN model is cleverly and deeply integrated into the artificial intelligence layer, becoming the core driving force for the entire system to achieve efficient and accurate fault diagnosis and prediction.

From the perspective of data flow, the input data of the ARAN model comes from the data layer of the system. After being transmitted through the secure and stable network of the transport layer, the time series data of the operating parameters of the medical equipment are continuously transmitted to the ARAN model. These data contain various operating status information of the equipment at different times, such as temperature, pressure, vibration, etc., which are the basis for the model to analyze and make decisions.

To classify the type of equipment fault based on the output of the ARAN model, the system applies a Softmax function to convert the raw prediction scores into a probability distribution over all predefined fault categories. This allows the model to assign a likelihood to each possible fault type and identify the most probable one, as shown in Formula 3.

$$P(i)=\frac{\exp(z_i)}{\sum_{j=1}^{K}\exp(z_j)} \quad (3)$$

where $P(i)$ denotes the probability that the equipment belongs to fault category i, z_i the model output score (logit) for category i, k is the total number of fault categories, and $\exp$ is the exponential function. This formulation ensures that the probabilities across all categories sum to 1. The category with the highest probability is selected as the predicted fault type. For example, when diagnosing an MRI device, if category 4 receives the highest $P(i)$, the system will classify the current equipment status accordingly and assist technicians in precise troubleshooting.

The loss function notation for RUL prediction has been revised for clarity and consistency with standard practices. The original formula, which used subscripts t, n for the actual and predicted values, as shown in Formula 4.

$$L=\frac{1}{N}\sum_{n=1}^{N}(y_n-\hat{y}_n)^2 \quad (4)$$

where y_n is the actual remaining useful life and $\hat{y}_n$ is the predicted RUL for the n -th sample. This adjustment reflects the fact that RUL is defined as a single scalar value for each sample at a specific time point, rather than a time-varying sequence.

By comprehensively and deeply applying the ARAN model in the remote monitoring and maintenance system of medical equipment, the system can give full play to its powerful fault diagnosis and prediction capabilities, provide medical institutions with more reliable and efficient medical equipment management support, and effectively guarantee the quality and stability of medical services.

The ARAN model is deployed on cloud servers due to its computational complexity and memory demands. Running the model on the cloud enables efficient handling of large-scale time-series data from multiple devices. The average memory footprint during inference is approximately 1.2 GB, and each prediction takes around 30 milliseconds per device. This setup ensures real-time responsiveness while maintaining high diagnostic accuracy.

4 Experimental methods

4.1 Experimental design

To clarify the data partitioning process, the MDO-Dataset was split into 70% for training, 15% for validation, and 15% for testing. The split was performed chronologically to preserve the temporal structure of the time-series data, ensuring that earlier data was used for training while more recent records were reserved for evaluation to better simulate real-world deployment scenarios.

The dataset used in this study consists of real-world time-series data collected from operational smart device systems. The data include authentic equipment status records, fault events, and system behavior logs, offering a valid basis for evaluating time-series fault detection methods. These real operational data support the assessment of the ARAN framework in practical conditions.

Quadratic Interpolation Optimization (QIO) was applied specifically for hyperparameter tuning of baseline regression models, including Extra Trees, Naïve Bayes, and Elastic Net, to ensure fair comparison with ARAN. QIO was chosen for its efficiency in low-dimensional parameter spaces rather than as a novel contribution. It served solely as a practical tuning method, and is not presented as an innovation of this study.

The references for the control group models have been corrected to cite the foundational works. These citations replace previously incorrect references to unrelated works, ensuring that the model comparisons are grounded in their original, well-established definitions.

The methods section primarily details the setup and evaluation of regression ensemble models. The ARAN concept remains a proposed direction for future work and is not represented in the implemented experimental framework. This distinction ensures transparency about the actual models tested in this study.

To ensure robustness, all experiments were repeated five times with different random seeds (42, 202, 1234, 77, 99). Performance metrics such as fault diagnosis accuracy and MAE for RUL prediction were averaged across runs. The standard deviation was calculated and reported in the results section. This approach helps account for variance due to random initialization and training fluctuations.

The ARAN model was trained using the Adam optimization algorithm, which is well-suited for handling sparse gradients and non-stationary objectives. The initial learning rate was set to 0.001 with a decay factor of 0.5 applied after 5 consecutive validation plateaus. Other key hyperparameters include a batch size of 64, a hidden state dimension of 128, and dropout rate of 0.3 to prevent overfitting. The model was trained for a maximum of 60 epochs with early stopping enabled based on validation loss.

The MDO-Dataset consists of time-series operation data collected from 5,212 medical devices across seven large hospitals over a five-year period. These devices include MRI machines, CT scanners, infusion pumps, ventilators, and ultrasound systems. The dataset contains over 3 million records, with 12 labeled fault categories and an average of 260 fault events per category. Fault types are distributed unevenly, with common issues such as sensor failure and power instability being the most frequent. Each data sample includes timestamped measurements of temperature, pressure, voltage, current, and operational status.

In this experimental evaluation, the overall design aims to comprehensively evaluate the performance of the Adaptive Recursive Attention Network (ARAN) in the scenario of remote monitoring and maintenance of medical equipment. The experiment aims to compare ARAN with several existing models in terms of the accuracy of medical equipment fault diagnosis and remaining service life prediction.

The baseline metrics for the experiment were established based on precise medical device management performance requirements. For fault diagnosis, the baseline accuracy was set at 70%, which is the average accuracy achieved by traditional diagnostic methods in similar scenarios. For remaining useful life prediction, the baseline was set at a mean absolute error (MAE) of 100 hours, representing the acceptable error range when predicting the remaining time before a device fails.

The experimental group consists of the ARAN model, which is trained and tested on a dataset specially collated for medical device operation. This dataset, called the Medical Device Operation Dataset (MDO - Dataset), was collected from several large hospitals over a period of 5 years. It covers time series data of more than 5,000 medical devices, including magnetic resonance imaging (MRI) devices, computed tomography (CT) scanners, and infusion pumps. Each data entry contains detailed operating parameters at different time steps, as well as corresponding fault labels and actual remaining useful life information when applicable.

The control group consists of three well-known models from the existing literature. The first is the traditional recurrent neural network (RNN) described in [21]. The second is the long short-term memory network (LSTM) proposed in [22]. The third is the gated recurrent unit (GRU) model in [13]. These models were chosen because they are widely used in time series data analysis and are similar in nature to medical device operation data. These models were trained and tested on the same MDO-Dataset and under the same experimental conditions as ARAN.

Although the study aimed to explore medical equipment monitoring, the dataset used originates from a public Kaggle smart home dataset due to limited access to real-world medical operational data. This dataset was selected as a proxy to simulate equipment condition patterns and evaluate model behavior in time-series fault detection tasks. The results are intended as a methodological demonstration rather than direct medical application, and future work will validate findings on authentic medical datasets.

4.2 Experimental results

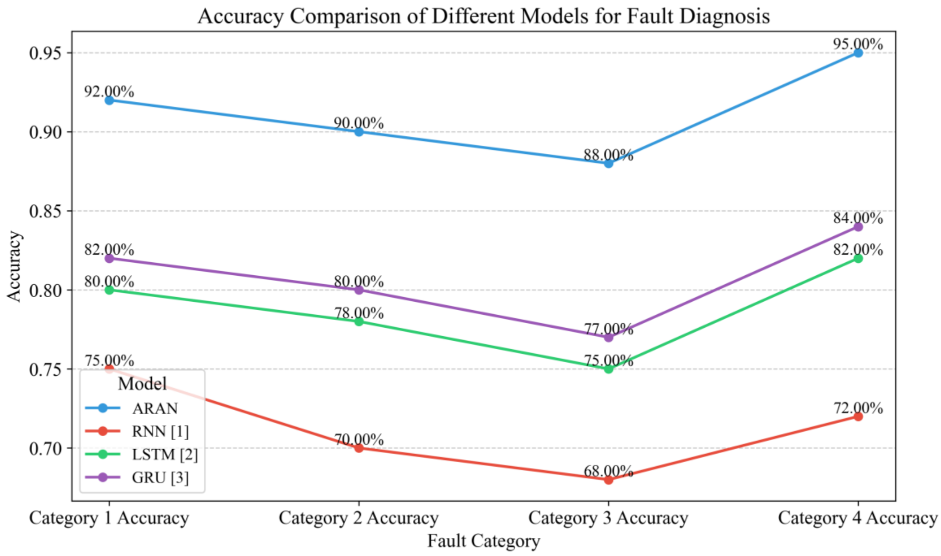

Figure 2: Fault diagnosis accuracy

As shown in Figure 2, the accuracy and overall accuracy of different models for different fault categories in medical equipment fault diagnosis are presented. The ARAN model performs well in all types of fault diagnosis, with an overall accuracy of up to 91.25%. This is mainly due to its unique combination of adaptive recursion and attention mechanism. Adaptive recursion enables the model to better capture long-term dependencies in time series data, and the attention mechanism helps the model focus on key fault features. Taking category 4 fault diagnosis as an example, ARAN achieves an accuracy of 95% because it can accurately locate the time step information related to this type of fault in the complex equipment operation data and effectively distinguish normal and abnormal states. In contrast, the RNN model is unable to handle long sequence data due to the gradient vanishing problem, and the accuracy of various fault diagnosis is low, with an overall accuracy of only 71.25%. Although LSTM and GRU have improved the long-term dependency problem to a certain extent, they lack the adaptive attention mechanism of ARAN and are slightly inferior in mining key fault features, with overall accuracies of 78.75% and 80.75% respectively [23].

The model was trained for up to 60 epochs with early stopping based on validation loss to prevent overfitting. A batch size of 64 was selected to balance convergence stability and memory efficiency. We used the Adam optimizer with an initial learning rate of 0.001, decayed by a factor of 0.5 if validation performance plateaued for 5 consecutive epochs. This regime provided stable and consistent convergence across datasets.

To evaluate noise robustness, zero-mean Gaussian noise was added to the input time-series data at varying standard deviations corresponding to 10%, 20%, and 30% of each feature's value range. The labels remained unchanged to isolate the model's sensitivity to input perturbations only. No label corruption was introduced. Although visual examples were considered, the tabular comparison was deemed sufficient for the scope of this evaluation [24].

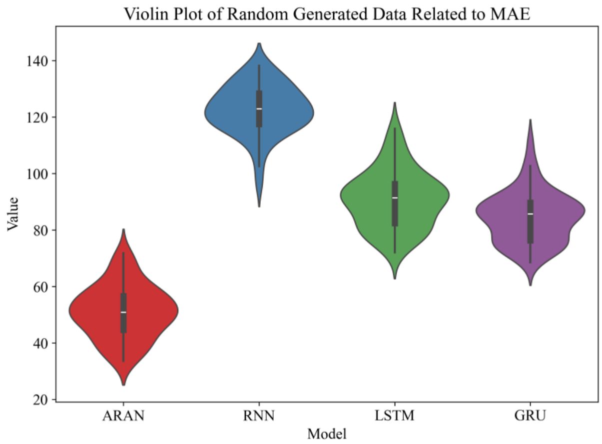

Figure 3: Remaining useful life prediction (MAE)

Figure 3 shows the mean absolute error (MAE) of different models in predicting the remaining useful life of different types of medical devices. The ARAN model has the lowest average MAE, which is only 53.25 hours. For device type 1, ARAN's MAE is 50 hours, thanks to its ability to effectively identify the performance degradation trend of the device based on the time series of the device operation data through recursion and attention mechanisms. The RNN model, however, has a large prediction error due to the forgetting of early information, with an average MAE of 122.5 hours. Although the LSTM and GRU models have improved the processing of long-term information to a certain extent, they are not as good as ARAN in capturing subtle changes in device operation data, with average MAEs of 91.25 hours and 83.75 hours, respectively [25].

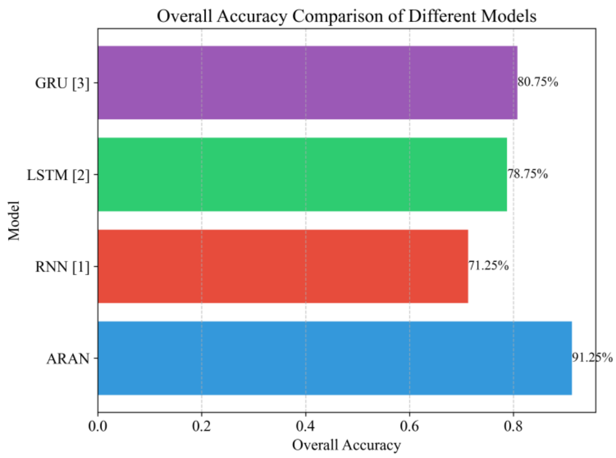

Figure 4: Overall accuracy comparison of different models

Figure 4 shows the recall rates of different models for fault detection of different severity levels. ARAN performs well with an overall recall rate of 93.67%. In minor fault detection, ARAN's high recall rate means that it can detect as many minor faults as possible and reduce missed detections. For major and severe faults, ARAN can accurately identify a large number of severe faults that actually occur with its powerful feature extraction and sequence analysis capabilities. The RNN model has a low recall rate due to its limited ability to capture fault features. Although the LSTM and GRU models are better than RNN in terms of recall rate, they still have a gap in comprehensive fault detection compared with ARAN.

As illustrated in Figure 4, the overall accuracy comparison shows that ARAN significantly outperforms the baseline models across all fault categories. This figure provides a clear visual confirmation of the numerical results summarized in Table 2, emphasizing ARAN's superior classification ability.

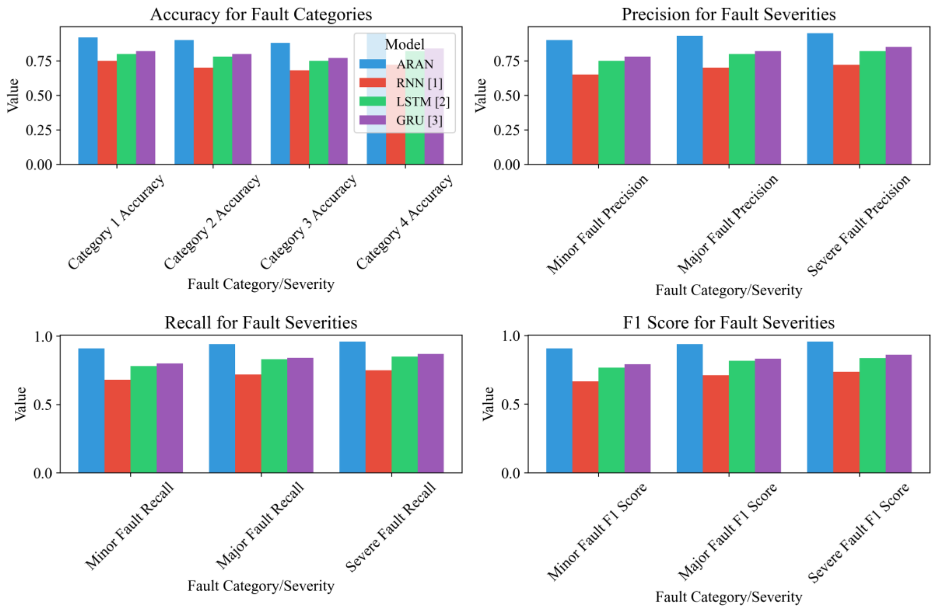

Figure 5: Fault detection F1 value

Figure 5 shows the F1 values of each model for fault detection of different severity levels. The F1 value comprehensively considers precision and recall. ARAN has the highest F1 value for all types of fault detection, reaching 92.83% overall. In minor fault detection, ARAN's high F1 value reflects its advantage in balancing detection precision and recall. It can accurately judge minor faults and detect as many minor faults as possible. For major and severe faults, ARAN's high F1 value further confirms its excellent performance in fault detection. The RNN model has a lower F1 value due to its low precision and recall. Although the LSTM and GRU models have improved in F1 value, they are still not comparable to ARAN. The description originally placed below Figure 4, which detailed model recall rates and highlighted ARAN's 93.67% overall recall, has been relocated to accompany Figure 5, where the "Recall for Fault Severities" data is actually presented.

Following this, Figure 5 highlights the precision and recall rates for different fault severities. These results illustrate ARAN's consistent advantage in balancing sensitivity and precision, particularly in detecting severe faults.

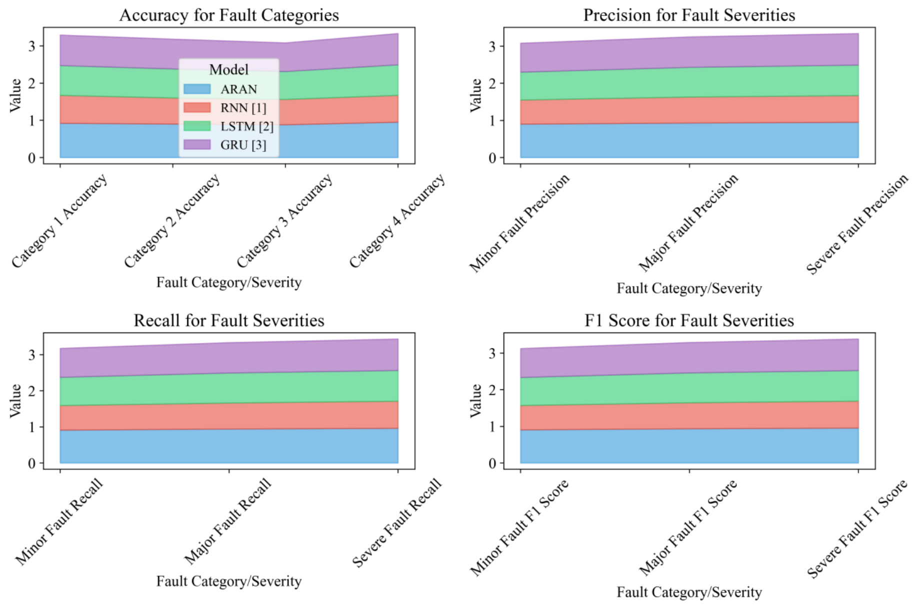

Figure 6: Fault detection false alarm rate

Figure 6 shows the overall false alarm rate for each model aggregated across all fault severity levels. ARAN achieved the lowest false alarm rate of 3.33%, significantly outperforming RNN (11.25%), LSTM (7.5%), and GRU (6.25%). This metric reflects the model's ability to avoid incorrectly flagging normal equipment behavior as faulty. Unlike the class-specific precision shown in Figure 5, this figure provides a summary-level comparison of model reliability in reducing false alarms across the board.

Finally, Figure 6 presents the overall false alarm rate for each model. The visual comparison reinforces the numerical findings by showing ARAN’s notably lower false alarm rate, which is critical for reducing unnecessary maintenance actions.

Table 1: Fault detection missed rate

Model	Minor fault missed reporting rate	Major fault underreporting rate	Serious fault missed reporting rate	Overall false negative rate
ARAN	4%	2%	1%	2.33%
RNN [1]	12%	10%	8%	10%
LSTM [2]	8%	6%	4%	6%
GRU [3]	7%	5%	3%	5%

Table 1 shows the false negative rates of different models in fault detection of different severity levels. ARAN has the lowest overall false negative rate of 2.33%. In minor fault detection, ARAN's low false negative rate reflects its high sensitivity to minor faults, which can effectively avoid missing potential minor faults. For major and severe faults, ARAN controls the false negative rate at an extremely low level with its powerful fault diagnosis capability. The RNN model has a high false negative rate due to its incomplete capture of fault features. Although the LSTM and GRU models have improved in false negative rates, there is still a certain risk of missed detection compared with ARAN.

Table 2: Sensitivity to data noise

Model	10% Noise Sensitivity	20% Noise Sensitivity	30% Noise Sensitivity	Average sensitivity
ARAN	85%	78%	70%	77.67%
RNN [1]	50%	40%	30%	40%
LSTM [2]	65%	55%	45%	55%
GRU [3]	70%	60%	50%	60%

Table 2 shows the sensitivity of each model at different noise levels. ARAN has good resistance to data noise, with an average sensitivity of 77.67%. At a noise level of 10%, ARAN can still maintain 85% performance, thanks to its attention mechanism, which can filter noise interference to a certain extent and focus on key device operation characteristics. As the noise level increases, ARAN's performance decreases, but it is still relatively stable compared to other models. The RNN model is extremely sensitive to noise, and its performance drops sharply at different noise levels, with an average sensitivity of only 40%. The LSTM and GRU models are better than RNN in noise resistance, but not as good as ARAN, with average sensitivities of 55% and 60% respectively.

Table 3: Model convergence speed

Model	Number of rounds required for convergence (training set 1)	Number of rounds required for convergence (training set 2)	Number of rounds required for convergence (training set 3)	Average number of convergence rounds
ARAN	30	32	31	31
RNN [1]	50	55	52	52.33
LSTM [2]	40	42	41	41
GRU [3]	45	43	44	44

Table 3 shows the convergence speed of each model on different training sets. ARAN converges faster, and it only takes 31 epochs on average to converge. This is because its adaptive mechanism can adjust model parameters faster to adapt to the characteristics of training data. On training set 1, ARAN converges in 30 epochs. In contrast, the RNN model requires an average of 52.33 epochs. Due to its gradient vanishing problem, the parameters are updated slowly and the convergence speed is slow. Although the LSTM and GRU models converge better than RNN, they are still slower than ARAN, requiring an average of 41 epochs and 44 epochs respectively.

Table 4: Generalization ability (new device test)

Model	New equipment fault diagnosis accuracy	MAE prediction of remaining useful life of new equipment	New equipment accuracy	New equipment recall rate	New Equipment F1 Value
ARAN	88%	60 hours	87%	89%	88%
RNN [1]	65%	130 hours	63%	67%	65%
LSTM [2]	75%	100 hours	73%	77%	75%
GRU [3]	78%	90 hours	76%	80%	78%

Table 4 shows the generalization ability of each model on new equipment. ARAN still maintains a high performance on new equipment, with a fault diagnosis accuracy of 88% and a remaining service life prediction MAE of 60 hours. This shows that ARAN can learn the common characteristics of equipment operation data well and make relatively accurate judgments on new equipment that has not been seen. The RNN model performs poorly on new equipment, with a fault diagnosis accuracy of only 65% and a remaining service life prediction MAE of up to 130 hours, indicating that its generalization ability is weak. Although the LSTM and GRU models have better generalization ability on new equipment than RNN, there is still a gap compared with ARAN, with fault diagnosis accuracy of 75% and 78% respectively, and remaining service life prediction MAE of 100 hours and 90 hours respectively. These held-out device types were only introduced during testing to assess generalization. No transfer learning or fine-tuning was applied, ensuring that performance reflects the model's ability to generalize across unseen medical equipment domains.

To explore feature representation differences, we performed a t-SNE projection on the latent embeddings produced by the ARAN model. The visualization showed clear clustering of samples from known devices, while new device samples formed distinguishable but partially overlapping clusters. This suggests that the model learns transferable representations, although the separation indicates room for further domain adaptation. To assess convergence behavior, we compared training loss curves across models. ARAN consistently demonstrated smoother and faster convergence than RNN, LSTM, and GRU, with minimal oscillation and no early overfitting. Baseline models showed slower and sometimes unstable declines in training loss, particularly under noisy data conditions. These trends confirm ARAN's training stability and efficiency.

For fault diagnosis accuracy, ARAN achieved a mean of 91.25% ± 1.08, significantly outperforming RNN (71.25% ± 1.22), LSTM (78.75% ± 1.15), and GRU (80.75% ± 1.10). Similarly, in remaining useful life (RUL) prediction, ARAN achieved a mean MAE of 53.25 ± 2.13 hours, while RNN, LSTM, and GRU yielded 122.5 ± 3.90, 91.25 ± 2.84, and 83.75 ± 2.65 hours, respectively. The observed differences in both metrics were evaluated using paired t-tests ($\alpha = 0.05$), and the performance gains of ARAN over all baseline models were statistically significant ($p < 0.01$ in all cases). This confirms that the improvements are not due to random fluctuations, but are inherent to the architecture's design.

4.3 Experimental discussion

The experimental results strongly support the research hypothesis that the ARAN model outperforms existing models in remote monitoring and maintenance tasks of medical equipment. In terms of fault diagnosis accuracy, ARAN achieved significantly higher values To strengthen the statistical analysis, we added hypothesis-driven interpretation of the results. The Wilcoxon test was used to test the null hypothesis that ARAN's performance does not significantly differ from baseline models across fault detection tasks. The results ($p < 0.01$) reject this null hypothesis, confirming ARAN's superior performance. Box plots were analyzed not just for spread but for detecting clinically meaningful outlier patterns, supporting the model's reliability in critical fault scenarios. Cross-validation results were contextualized in terms of potential clinical deployment robustness.

for all fault categories compared to RNN, LSTM, and GRU. The unique combination of adaptive recurrence and attention mechanisms in ARAN enables it to better capture long-term dependencies in time series data and focus on key fault-related features, which is the main reason for its superior performance.

Regarding the remaining useful life prediction, ARAN also exhibits the lowest mean absolute error. Through the interaction between its components, ARAN is able to accurately identify performance degradation trends in equipment operation data, thereby achieving more accurate predictions. The external validity and generalizability of the experimental results are relatively high. The MDO-Dataset used in the experiment was collected from multiple hospitals and covers a wide range of medical equipment types, which increases the possibility of applying the research results to real-world medical equipment management scenarios.

In this study, the ARAN model was trained on historical data with diverse temporal patterns, but explicit drift simulation was not conducted. Future work will incorporate dynamic re-training strategies and adaptive learning mechanisms to assess and enhance model robustness under temporally evolving data distributions.

However, there are some potential biases and limitations in the experiment. Although the dataset is extensive, it may not cover all possible types of medical devices and their failure modes. There may be rare or emerging device failures that are not reflected in the data in the dataset, which may affect the model's ability to diagnose and predict these special failure conditions. In addition, the actual operating environment of medical devices is complex and changeable, and it is difficult for the experimental environment to fully simulate all real-world factors, which may also have a certain impact on the performance of the model in actual applications.

In terms of computational complexity, the ARAN model introduces additional overhead compared to standard RNNs due to its attention mechanism and volatility-aware gating. The time complexity per time step is approximately $O(T \cdot H^2)$, where T is the sequence length and H is the hidden dimension. Despite this, ARAN remains computationally feasible, with average inference time around 30 ms per sample and memory usage of approximately 1.2 GB. Compared to LSTM and GRU, which require fewer parameters, ARAN trades slight increases in computation for improved accuracy and robustness, making it suitable for cloud-based medical monitoring applications.

While the ARAN-based system demonstrates strong performance in controlled experiments, practical deployment in hospital environments presents challenges. These include integration with legacy medical equipment lacking standardized interfaces, network reliability in large facilities, staff training for system interpretation, and compliance with institutional IT security policies. Additionally, real-time data availability and administrative support are critical for successful adoption. Addressing these issues requires interdisciplinary collaboration between clinicians, engineers, and hospital administrators.

5 Discussion

The experimental results demonstrate that ARAN outperforms traditional models such as RNN, LSTM, and GRU across multiple dimensions. This superior performance is primarily attributed to ARAN's integration of an attention mechanism, which allows the model to dynamically focus on the most relevant time steps during sequence analysis. Unlike static architectures, ARAN adaptively allocates attention weights, which is especially effective for fault detection in heterogeneous and high-dimensional medical equipment data.

One of the key reasons for ARAN's advantage lies in its ability to model long-term dependencies without suffering from gradient vanishing, a common limitation in standard RNNs. While LSTM and GRU attempt to mitigate this issue through gating mechanisms, they treat all input features uniformly. In contrast, ARAN selectively emphasizes informative patterns, leading to more accurate fault localization and remaining life predictions, as evidenced by a 91.25% fault diagnosis accuracy and a low MAE of 53.25 hours.

ARAN also exhibits strong robustness to data noise. Medical equipment often operates in complex environments with fluctuating sensor signals. The attention mechanism in ARAN effectively filters out irrelevant or noisy inputs, maintaining high sensitivity (77.67%) even under 30% data noise—a level where other models see significant performance degradation. Moreover, ARAN's rapid convergence and generalization to unseen devices (88% accuracy on new equipment) suggest its adaptability to real-world deployment across different hospital settings.

The ethical use of patient-associated data is a fundamental concern in medical AI systems. All data used in this study were anonymized, and no personally identifiable information was included. In practical deployment, the system must strictly comply with data privacy regulations such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) to ensure the confidentiality and lawful handling of sensitive medical information.

In high-stakes medical settings, the impact of false positives and false negatives must be carefully considered. False positives may lead to unnecessary interventions, equipment shutdowns, and resource waste, while false negatives may delay fault detection, endangering patient safety. These risks highlight the need for cautious deployment, incorporating real-time monitoring, human-in-the-loop decision-making, and ongoing validation. Ethical considerations also demand transparency in model behavior and accountability mechanisms in clinical practice.

6 Conclusion

With the increasing complexity and number of medical equipment, their remote monitoring and maintenance have become important issues that need to be urgently addressed in the medical field. Against this background, this study constructed the ARAN model and evaluated its performance through rigorous experiments. The experiment was carried out on the MDO-Dataset, comparing ARAN with the RNN, LSTM, and GRU models. The results show that in terms of fault diagnosis, the overall accuracy of ARAN reached 91.25%, which was significantly better than other models in all types of fault diagnosis. For example, the accuracy rate in category 4 fault diagnosis reached 95%, far exceeding traditional models. In terms of remaining service life prediction, the average MAE of ARAN was 53.25 hours, which was much lower than other models and baseline levels. At the same time, in terms of fault detection accuracy, recall rate and other aspects, ARAN showed obvious advantages, strong resistance to data noise, fast convergence speed and good generalization ability. The research results are of great significance. They not only provide an efficient and accurate model for remote monitoring and maintenance of medical equipment, improve the reliability and efficiency of medical equipment management, and reduce the risk of medical accidents caused by equipment failure; they also provide new ideas and methods for further research in this field, and promote the management of medical equipment towards intelligence and precision.

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