



Enhanced accident diagnosis for molten salt reactors using an adaptive residual CNN with Bayesian optimization

Chao-Qun Wang^{1,2} · Kai Wang^{1,2} · Qun Yang^{1,2} · Rong-Jian Liang¹ · Xin Yue¹ · Liang-Jie Sun^{1,2} · Wen-Tao Jiang^{1,2} · Zhao-Zhong He¹ · Na-Xiu Wang^{1,2}

Received: 15 January 2025 / Revised: 1 April 2025 / Accepted: 7 April 2025 / Published online: 22 May 2026

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Abstract

Safety is of paramount importance in nuclear power plants. Accurate and reliable accident diagnosis is essential for ensuring operational safety in reactor systems. The convergence of Industry 4.0 technologies and deep learning methods has emerged as a promising approach for improving the operational safety of nuclear energy systems, particularly in fault detection and diagnosis (FDD) applications. This study proposes a novel adaptive accident diagnosis framework tailored for molten salt reactors (MSRs) based on an enhanced residual convolutional neural network (AM-RCNN). The AM-RCNN incorporates an anti-noise module implemented using the soft thresholding method, together with an attention mechanism, to improve robustness. Datasets representing eight distinct operational scenarios were generated using the RELAP5-TMSR simulation tool. An appropriate subset of input features for MSR accident diagnosis was selected using Pearson correlation analysis and random forest importance ranking. The models were subsequently trained, validated, optimized, and tested. Comparative analyses with conventional RCNN and CNN architectures demonstrate the diagnostic advantages of the proposed approach. In addition, the integration of Bayesian optimization further enhances the performance of the AM-RCNN. As a contribution to intelligent monitoring research for MSRs, the proposed method provides reliable decision support for nuclear system operation, particularly in autonomous scenarios.

Keywords Accident diagnosis · Feature selection · Deep residual CNN · Bayesian optimization · Molten salt reactors

1 Introduction

Escalating global energy consumption exacerbates climate change, underscoring the critical need for carbon emission mitigation strategies to address environmental challenges [1]. As a nearly carbon-free power source, nuclear energy plays a significant role in mitigating the global

greenhouse effect and addressing global warming [2, 3]. The widespread implementation of nuclear energy relies predominantly on nuclear power plants (NPPs) that harness nuclear fission reactions. Compared with traditional energy sources, NPPs have more stringent safety requirements owing to their complex nature and the potential hazards associated with radioactive materials [4].

In pursuit of nuclear reactor designs with enhanced safety and economic viability, the Generation IV International Forum (GIF) proposed six reactor technologies for future development, among which molten salt reactors (MSRs) are considered a promising alternative [5–8]. MSRs exhibit exceptional inherent safety characteristics owing to their unique design and operating principles. In these reactors, liquid molten salt serves a dual function as both the nuclear fuel carrier and primary coolant, efficiently transferring heat from the core [9]. The safety advantages of MSRs are reflected in several aspects: (1) operation at near-atmospheric pressure, (2) strong negative reactivity temperature

This work was supported by the Youth Innovation Promotion Association (YIPA) of the Chinese Academy of Sciences (No. E329290101).

✉ Qun Yang
yangqun@sinap.ac.cn

✉ Na-Xiu Wang
wangnaxiu@sinap.ac.cn

¹ Shanghai Institute of Applied Physics, Chinese Academy of Sciences, Shanghai 201800, China

² University of Chinese Academy of Sciences, Beijing 100049, China

feedback combined with a large void coefficient [10, 11], (3) low proliferation risk, and (4) immunity to fuel irradiation damage or mechanical failure [12–15]. Despite these inherent safety features, potential risks associated with operational anomalies and accidents remain significant concerns. Therefore, accurate and timely accident diagnosis is essential to prevent the escalation of abnormal events and mitigate their consequences, serving as an external safeguard for reactor operation.

Currently, accident diagnosis in NPPs relies primarily on conventional threshold-monitoring approaches and human expertise [16]. Although operators are typically well trained, they may experience significant psychological stress during NPP accidents, making it challenging to accurately assess the nature of an accident within a limited time frame. Consequently, further research on accident diagnosis technologies for nuclear energy systems is urgently needed. Developing systems capable of accurately and efficiently identifying accidents is essential for supporting prompt decision-making during emergency response.

Accident diagnosis strategies for NPPs are generally classified into two methodological approaches: model-driven and data-driven. Model-based methods require the formulation of precise mathematical representations that capture the fundamental physical principles governing system behavior [17]. The continuous evolution of industrial technologies and computational capabilities has propelled modern nuclear systems toward increasingly sophisticated architectures characterized by large-scale designs, complex structures, and distributed configurations [18]. However, the inherent complexity of nuclear phenomena, coupled with uncertainties in input parameters [19], poses significant challenges for developing high-fidelity models capable of accurately representing the behavior of these advanced systems.

Data-driven methodologies, in contrast, establish diagnostic frameworks through statistical analysis of operational data, thereby eliminating the requirement for explicit modeling of complex parameter interactions [20]. Such approaches exploit the inherent correlations among system parameters by developing data-driven models in which complex interdependencies are automatically captured during the training process. This paradigm has led to extensive research and practical applications of machine learning techniques in nuclear system diagnostics, including support vector machines (SVMs) [21], ensemble decision trees (DTs) [22], k -nearest-neighbor (KNN) algorithms [23], artificial neural networks (ANNs) [24, 25], and multivariate statistical analysis [26].

However, with the rapid advancement of artificial intelligence (AI), along with the deployment of advanced sensors and high-speed data transmission mechanisms, operational datasets reflecting reactor status have begun to exhibit big data characteristics. These developments have

rendered conventional data-driven methods potentially insufficient for the demands of the emerging nuclear big data era. To address these limitations, deep learning architectures have emerged as a viable solution with remarkable capabilities for diagnosing anomalies and accidents in nuclear systems [27–30].

Among deep learning architectures, convolutional neural networks (CNNs) have gained significant attention in fault diagnostic applications owing to their strong capability for extracting high-dimensional and complex features [31]. For example, researchers have developed an enhanced CNN architecture incorporating mini-batch processing optimization, which has been successfully implemented in nuclear system diagnostics, achieving higher accuracy and providing valuable guidance for operators [32]. Additionally, a multiclassification framework based on a CNN architecture was developed to detect core disturbances and abnormal operational signatures, demonstrating high robustness and practical potential [33]. In a recent study, an SSA-CNN-LSTM model for NPP fault diagnosis was proposed, achieving a classification accuracy of 98.24% through CNN-LSTM parameter optimization using the sparrow search algorithm, thereby enhancing nuclear safety and reducing hazards caused by human error [34].

However, a persistent limitation of conventional deep learning architectures is performance degradation as the network depth increases, which can adversely affect classification accuracy [35]. This issue has been addressed by introducing deep residual CNNs (ResNets) [36]. Compared with traditional CNNs, ResNets employ identity shortcut connections that reduce the difficulty of training deep architectures, thereby improving the model's discriminative capability for complex classification tasks. As a result, ResNets have gradually gained popularity in fault diagnosis applications [37–41].

For example, adaptive wavelet transform features have been integrated with the ResNet architecture to enhance the fault detection capability of planetary gear transmission systems [37]. Sun and Wang developed several diagnostic models by integrating multilayer perceptrons (MLPs), CNNs, recurrent neural networks (RNNs), and ResNets, and compared their performance using a dataset from Case Western Reserve University [38]. Zhao et al. adopted an adaptive parametric rectified linear unit (ReLU) in ResNet to improve feature learning capability, which was validated through fault diagnosis applications [40]. Yao et al. proposed an innovative diagnostic framework incorporating adaptive residual convolutional networks specifically designed for anomaly identification in small modular reactor (SMR) operational systems [41].

These studies provide useful references for applying the residual CNN (RCNN) method to diagnostic tasks in the

nuclear energy field. However, several issues still require further consideration and improvement:

- (1) Nuclear energy systems consist of numerous subsystems and a large number of monitoring parameters. These datasets often exhibit high-dimensional characteristics, posing significant challenges for data analysis and decision-making. To improve model learning efficiency and performance, feature selection techniques should be implemented to identify the optimal feature subset for classification.
- (2) In practical applications, data collected in NPPs are often contaminated by noise. Therefore, it is necessary to combine the RCNN structure with an attention mechanism to enhance the model's robustness to noise.
- (3) In NPPs, different accidents may exhibit similar signals during their early stages. RCNNs typically use ReLUs as activation functions, which have a constant slope and zero output in the negative region. This property may reduce effective feature learning capability, thereby limiting model performance. Therefore, an activation function with more dynamic parameters should be incorporated into the model to enhance classification capability.
- (4) Hyperparameter optimization is essential for improving the performance of deep learning models. An in-depth investigation of hyperparameters should therefore be conducted for the proposed network to maximize its effectiveness.

To address the aforementioned challenges and improve accident diagnosis efficiency in nuclear energy systems, this study proposes a three-step methodology. First, Pearson correlation analysis and random forest importance ranking are used for feature selection. Next, a modified RCNN framework, termed an adaptive anti-noise module RCNN (AM-RCNN), is developed for MSR accident diagnosis by integrating an anti-noise module and adaptive parametric ReLUs. Finally, Bayesian optimization (BO) is applied to adjust the model's hyperparameters.

The remainder of this paper is organized as follows. Section 2 outlines the methodological framework of the proposed approach. Section 3 presents the case study for the nuclear accident diagnosis model. Section 4 compares the results with those of alternative models and describes the optimization process. Finally, Sect. 5 concludes the paper with key findings and potential directions for future research.

2 Methodology

2.1 Feature selection technique

Feature selection is a methodological approach for extracting the most relevant subset of attributes from a comprehensive feature space based on predefined optimization criteria and statistical evaluation metrics. This process aims to retain only the most relevant features from a dataset, thereby reducing the scale of data processing by eliminating redundant and irrelevant variables.

2.1.1 Pearson correlation coefficient

The Pearson correlation coefficient is a widely used statistical measure for feature selection tasks, quantifying the degree of linear dependence between paired variables. This metric evaluates the strength of the association between two random variables by analyzing their joint variability, which is represented through their covariance structure. Mathematically, the Pearson correlation coefficient for variables α and β can be expressed as Eq. (1) [42], where $\text{cov}(\alpha, \beta)$ represents the joint variability between variables α and β , and $\text{var}(\alpha)$ and $\text{var}(\beta)$ denote the variances of the respective variables.

$$\text{Corr}(\alpha, \beta) = \frac{\text{cov}(\alpha, \beta)}{\sqrt{\text{var}(\alpha) \times \text{var}(\beta)}} \quad (1)$$

The Pearson correlation coefficient ranges from -1 to 1 . A correlation value of zero ($\text{Corr}(\alpha, \beta) = 0$) indicates no linear dependence between variables α and β . Negative values ($\text{Corr}(\alpha, \beta) < 0$) indicate an inverse linear relationship, whereas positive values ($\text{Corr}(\alpha, \beta) > 0$) indicate a direct linear relationship. The strength of the linear association is reflected by the absolute magnitude of the coefficient, with values closer to unity indicating stronger statistical relationships between the variables.

2.1.2 Random forest variable importance

Random forests are a class of nonlinear predictive models that aggregate multiple decision trees for regression or classification tasks. Individual trees within the ensemble are generated using a bootstrap sampling process, in which each tree is constructed from an independently drawn random subset of the training data.

Random forest models provide variable importance measures that help identify features contributing significantly to class separation. Among these measures, permutation importance is one of the most commonly used approaches. This method sequentially shuffles the values of each predictor

variable and evaluates the corresponding reduction in the predictive performance of the model. Shuffling a variable disrupts its relationship with the outcome; therefore, a substantial decrease in classification accuracy after permutation indicates a strong predictive relationship between that feature and the target variable.

The permutation-based importance score $\omega_j(T_L)$ for each variable is computed using the following formula [43]:

$$\omega_j(T_L) = a(T_{L(\theta)}) - a(T_{L_{\text{oob}}^j(\theta)}), \quad (2)$$

where a represents the model accuracy, $L(\theta)$ denotes a distinct bootstrap sample, and $L_{\text{oob}}^j(\theta)$ corresponds to the out-of-bag (oob) samples with the j th feature randomly shuffled.

For tree ensembles, the importance scores from individual trees can be averaged to obtain an overall measure of feature importance [43].

$$\omega_j = \frac{1}{K} \sum_{k=1}^K \omega_j(T_{L(\theta_k)}) \quad (3)$$

2.2 Residual convolutional neural networks (RCNNs)

CNNs represent a class of deep-learning architectures that employ multiple filters to hierarchically process input samples through convolution and pooling operations across successive layers [27]. Building on this concept, RCNNs introduce skip connections to effectively address the model degradation problem [35, 36]. Instead of relying solely on deeper network structures to approximate complex hidden nonlinearities, RCNNs facilitate the learning of residual representations, which simplifies the optimization process. The architectural configuration of RCNNs is illustrated in Fig. 1.

The transformation from input to output can be expressed as follows [36]:

$$y = H(x) = F(x) + x \quad (4)$$

where $H(x)$ represents the composite mapping learned by the network layers, $F(x)$ corresponds to the residual function, and x denotes the input features. The residual function $F(x)$

is often parameterized as $F(x, \{W_i\})$ to explicitly indicate its dependence on both the input and the learnable weights. Accordingly, the n th residual block can be formulated as follows [36]:

$$y_n = H(x_n) = F(x_n, \{W_n\}) + x_{n1} \quad (5)$$

$$x_{n+1} = f_{\text{ReLU}}(y_n). \quad (6)$$

In this formulation, x_n and x_{n+1} represent the input and output feature maps of the n th residual module in the network architecture, respectively. The identity mapping is captured by $H(x_n)$, whereas f_{ReLU} denotes the ReLU activation function. According to Eq. (6), the feature propagation from the n th to the N th layer can be expressed as [36]:

$$x_N = x_n + \sum_{i=n}^{N-1} F(x_i, W_i). \quad (7)$$

In deep network architectures, the backpropagated gradient can be expressed as [36]:

$$\frac{\partial \text{loss}}{\partial x_n} = \frac{\partial \text{loss}}{\partial x_N} \cdot \left(\frac{\partial x_N}{\partial x_n} \right) = \frac{\partial \text{loss}}{\partial x_N} \left(1 + \frac{\partial}{\partial x_n} \sum_{i=n}^{N-1} F(x_i, W_i) \right). \quad (8)$$

Here, $\frac{\partial \text{loss}}{\partial x_n}$ denotes the gradient propagated through the n th layer. The identity term 1 in this equation enables direct gradient propagation without attenuation. While the residual component must pass through weighted layers, potentially modifying the gradient, the constant identity term ensures stable gradient flow. Even when the residual gradient approaches zero, the presence of this identity term prevents the gradients from vanishing.

2.3 Anti-noise module

In this study, an anti-noise (AN) architecture that combines a soft threshold function with an attention mechanism integrated into an RCNN is proposed. The resulting framework, termed AM-RCNN, enhances noise robustness in MSR accident diagnosis.

The soft thresholding (ST) operator is a widely adopted denoising technique in signal processing applications. Its fundamental principle involves threshold contraction: When the input exceeds a predefined threshold value, the output approaches this boundary; otherwise, it is set to zero. This mechanism effectively suppresses noise interference while preserving signal characteristics. The mathematical representation is as follows [44]:

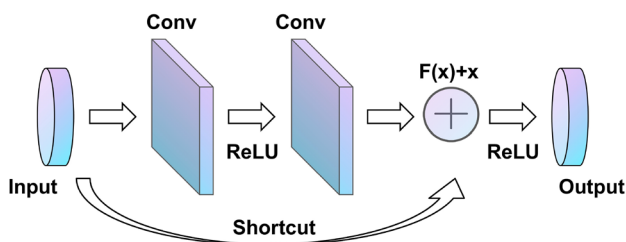


Fig. 1 (Color online) RCNN architecture

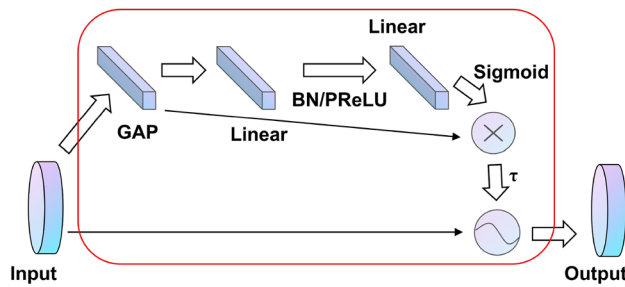


Fig. 2 (Color online) The architectural configuration of the anti-noise module (in the red box)

$$\text{Soft}(x, \tau) = \begin{cases} x - \tau, & \text{if } x > \tau, \\ 0, & \text{if } -\tau \leq x \leq \tau, \\ x + \tau, & \text{if } x < -\tau. \end{cases} \quad (9)$$

In conventional implementations, the threshold parameter τ typically requires manual configuration by system engineers prior to network deployment. In this study, the threshold is computed using an attention mechanism [45] that can be trained within the network and updated adaptively. The architectural configuration of the AN module is illustrated in Fig. 2.

The global average pooling (GAP) operation in this sub-module computes channel-wise mean values while preserving essential feature information. Parallel to this path, a compact network processes the GAP outputs through two sequential fully connected layers, culminating in a sigmoid activation function that generates scaling factors within the $[0, 1]$ range. This auxiliary network incorporates batch normalization and PReLU layers for feature normalization and nonlinear activation, respectively. The resulting adaptive threshold τ is obtained by multiplying the GAP-derived averages by the scaling coefficients produced by the compact network.

2.4 Bayesian theory-based optimization

Hyperparameters play a crucial role in machine learning algorithms because they directly influence the training process and significantly affect model performance. Tuning these hyperparameters often requires professional knowledge and expert experience. Consequently, hyperparameter tuning represents a challenging optimization problem with an implicit objective function. BO is a powerful approach for addressing such optimization problems [46]. Figure 3 presents the workflow of BO.

The BO process begins by defining the hyperparameter space, which encompasses the feasible value ranges for each tunable parameter. The optimization procedure then begins by sampling an initial set of configurations for model

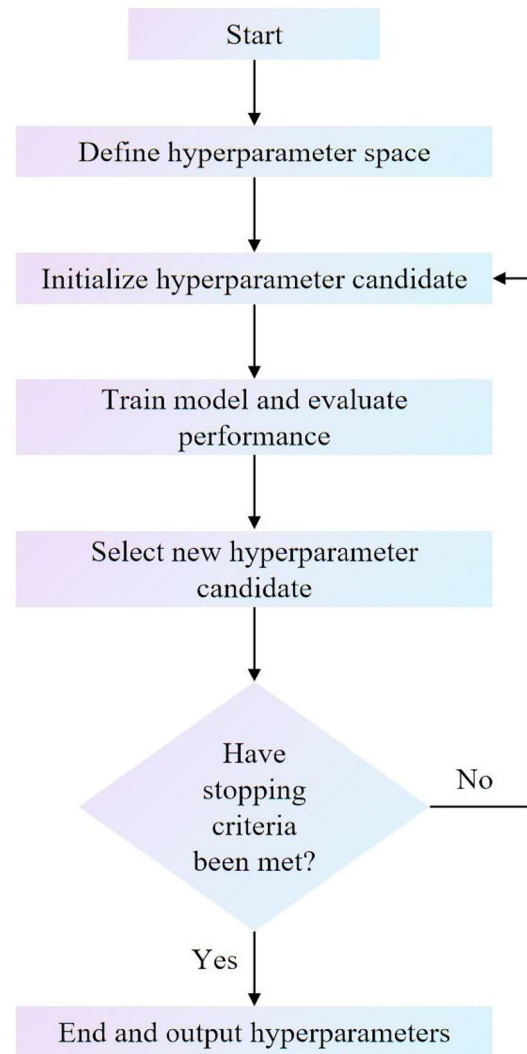


Fig. 3 (Color online) BO workflow

training and validation. Following performance evaluation, an acquisition strategy determines the next parameter combination for evaluation, guided by probabilistic surrogate models.

This process iterates through successive cycles, refining the parameter selection based on the performance observed in previous iterations. The iterative procedure continues until a predefined termination condition is satisfied. Once this condition is met, the optimization process concludes by identifying the hyperparameter configuration that yields the best model performance.

To provide a comprehensive and intuitive visualization of the computational procedure, a flowchart summarizing the integrated methodology is presented in Fig. 4. The flowchart illustrates the step-by-step procedure of the proposed methodology. The process begins with feature selection using Pearson correlation analysis and random forest importance

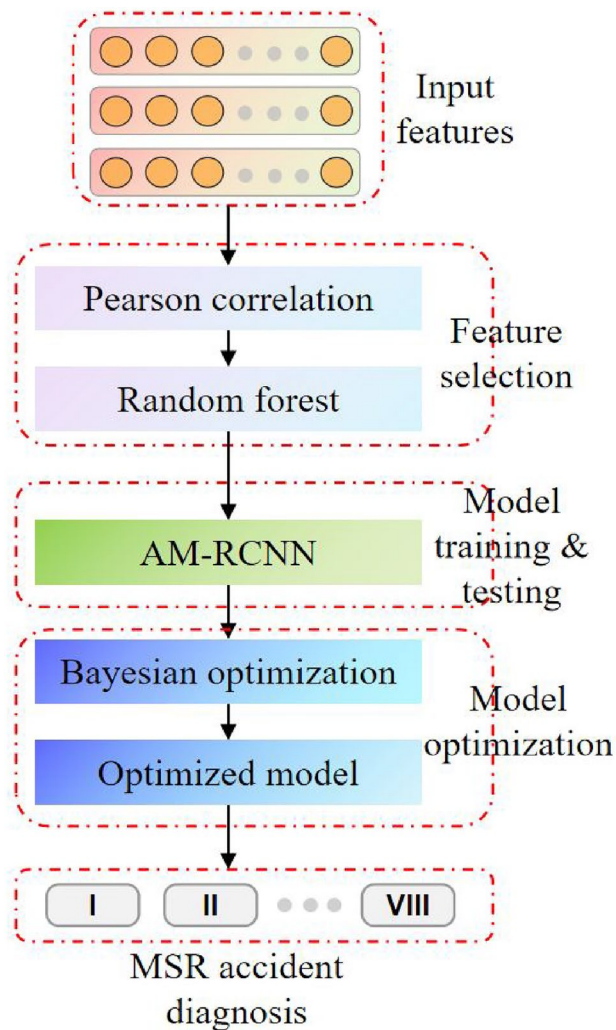


Fig. 4 (Color online) Flowchart of the proposed methodology

ranking, followed by the construction and training of the AM-RCNN model. BO is then applied to fine-tune the model's hyperparameters, ultimately yielding an optimized diagnostic model for MSR accident scenarios.

3 Case study

3.1 A designed MSR description

In 2011, the Chinese Academy of Sciences (CAS) initiated a strategic research program focusing on advanced nuclear fission energy systems, in which MSR technology represented a key development pathway. As part of this initiative, the TMSR program [5], a pioneering effort in MSR technology development, was conducted by the Shanghai Institute of Applied Physics (SINAP), CAS. The MSR investigated in this study corresponds to the design version proposed in the

TMSR program [47–49]. Figure 5 illustrates the conceptual design of the reactor, and Table 1 summarizes its key technical specifications [50].

The reactor adopts a dual-loop molten salt configuration. The primary loop, designated as the fuel–salt system, comprises a core vessel, primary heat exchanger, circulation pump, and connecting piping. The fuel salt circulates upward from the bottom plenum through the core and then flows into the shell side of the heat exchanger via the circulation pump. Thermal energy is subsequently transferred to the secondary loop, after which the cooled fuel salt completes the cycle by returning to the bottom plenum.

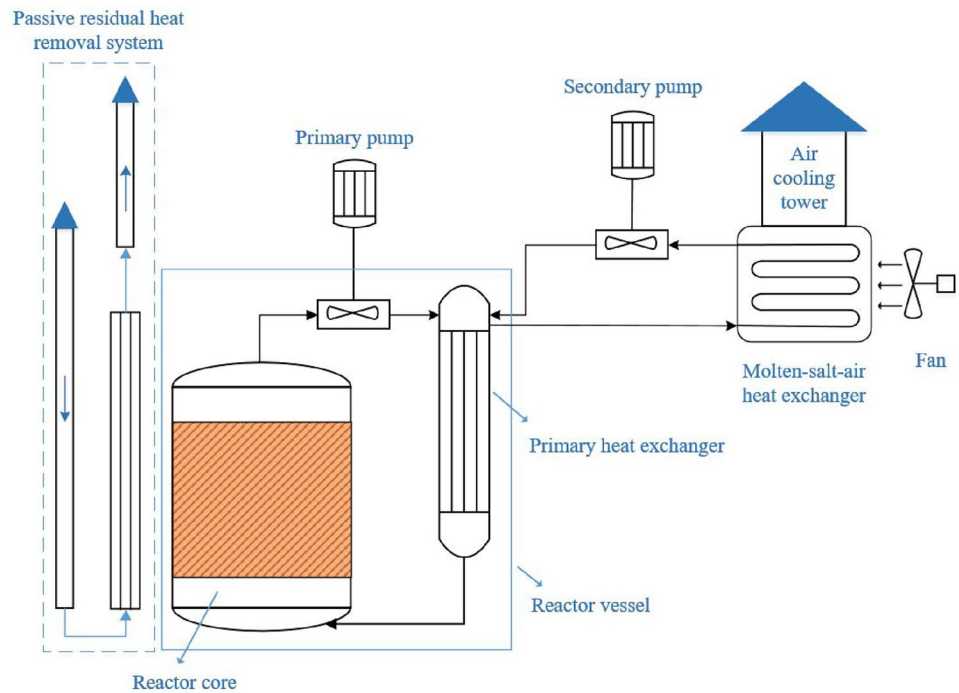
The secondary loop, referred to as the coolant salt system, contains a circulation pump, air-cooled heat exchanger, and associated piping. The coolant salt flows through the tube side of the primary heat exchanger, absorbs thermal energy from the primary loop, and releases heat to the atmosphere through the air-cooled exchanger. Furthermore, the MSR design incorporates a passive reactor vessel air cooling system (RVACS) for effective decay heat removal.

3.2 Operation scenario data collection

Given the limited availability of operational data for MSRs, accident diagnosis datasets were generated using the RELAP5-TMSR simulation code. This specialized tool, developed at SINAP [51, 52], extends RELAP5/MOD4.0 with enhanced capabilities for liquid-fueled reactor analysis. The accuracy of the code has been verified through experiments conducted on a high-temperature molten salt natural circulation test bench [53, 54], and it is currently applied in the design and analysis of MSR systems. Figure 6 illustrates the nodal configuration, where the primary circuit components are labeled 0XX, while 1XX and 2XX denote the secondary loop and the air cooling system, respectively. The RVACS is modeled using nodes 301–306.

In this study, eight typical operational scenarios are considered: one steady-state condition and seven transient events. By training the model using data that include both steady-state and transient conditions, the model's generalization capability is improved, enabling comprehensive accident detection across a wide range of operating states. Table 2 lists these operational conditions.

Given the varying transient characteristics at different power levels, each scenario was generated at reactor power levels ranging from 10% to 120% of full power (FP) in increments of 10% FP. The resulting dataset comprised more than 550,000 data samples, with each sample consisting of 21 monitoring parameters aligned with the architecture of the instrumentation and control system. The data-partitioning scheme allocated 70% of the dataset for model training, while equal proportions of 15% were reserved for validation and testing.

Fig. 5 (Color online) The conceptual design of the reactor**Table 1** Key technical specifications of the MSR design

Main parameter	Design value
Thermal power	2 MW _{th}
Fuel salt flow rate	50 kg/s
Fuel salt temperature (inlet/outlet)	630°C/650°C
Coolant salt flow rate	42 kg/s
Coolant salt temperature (inlet/outlet)	560°C/580°C

Additionally, to prevent the diagnostic system from ignoring variables with small absolute values caused by differences in measurement scales, the Z-score normalization method was adopted [55].

3.3 Feature selection

The 21 monitored parameters are listed in Table 3.

Assuming that all monitoring parameters are used as input features would impose a substantial computational burden, thereby compromising the efficiency and performance of the model. Therefore, feature selection was performed to reduce redundant variables among these parameters.

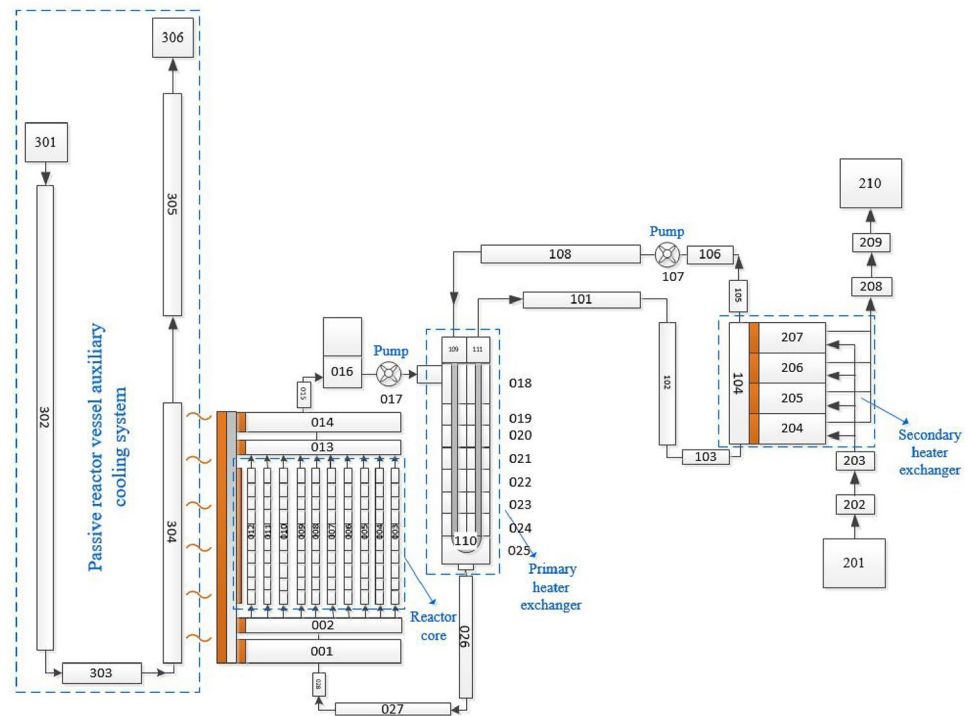
Reactor monitoring systems typically generate multiple interdependent parameters in which strong correlations may exist (e.g., perfectly correlated variables contain redundant information and can be represented by a single parameter). Therefore, the Pearson correlation metric was used as the primary statistical tool to quantify the linear dependence among system variables. The Pearson correlation coefficients

between variables are shown in Fig. 7, where features 0–20 correspond to the parameters are listed in Table 3.

A Pearson correlation coefficient with an absolute value exceeding 0.8 is commonly considered to indicate a strong correlation between two parameters [56]. However, this threshold should be evaluated within the specific context of the application. In practical scenarios, when two parameters exhibit strong correlation, preference is typically given to retaining the parameter that is easier to measure and has higher measurement accuracy.

Following this principle, a parameter-screening process was conducted to evaluate parameter significance across three correlation thresholds: $|r| > 0.8$, $|r| > 0.9$, and perfect linear correlation ($|r| = 1$). The results indicate that selecting a threshold greater than 0.9 for parameter retention yields optimal model performance. Accordingly, the input feature subset filtered using the Pearson correlation coefficient comprises seven parameters: reactor power; fuel circulating pump speed (FCPS); coolant circulating pump speed (CCPS); inlet, middle, and outlet temperatures of the reactor core (CIT, MCT, and COT); and the inlet temperature of the primary heat exchanger tube side (TITHE).

Uncorrelated features in machine learning models may act as noise sources, potentially reducing model accuracy by introducing classification bias. The random forest variable importance method was therefore applied to identify the relevance between variables and classes. The evaluation and ranking of feature importance are shown in Fig. 8. To ensure that the selected features effectively support the model's diagnostic capability, scenarios with relative

Fig. 6 (Color online) MSR nodal configuration diagram**Table 2** Operational conditions

Operation scenario	Description
I (normal)	Steady state
II (accident)	Uncontrolled withdrawal of a control rod (shim rod)
III (accident)	Uncontrolled withdrawal of a control rod (regulating rod)
IV (accident)	Coolant circulating pump rotor seizure
V (accident)	Loss of air flow of the molten salt-air heat exchanger
VI (accident)	Fuel circulating pump speed increases unexpectedly
VII (accident)	Coolant circulating pump speed increases unexpectedly
VIII (accident)	Loss of offsite power

importance thresholds of 0.05 and 0.10 were examined during the parameter-screening process. Rigorous testing indicated that the model achieved the best performance with a threshold of 0.05. Consequently, all seven parameters were retained in the final feature set to preserve diagnostic accuracy and ensure robust system performance.

3.4 Model structure and hyperparameter setting

The structure of the AM-RCNN model for MSR accident diagnosis, which integrates advanced deep-learning methodologies, is shown in Fig. 9, and Table 4 provides details of the AM-RCNN architecture.

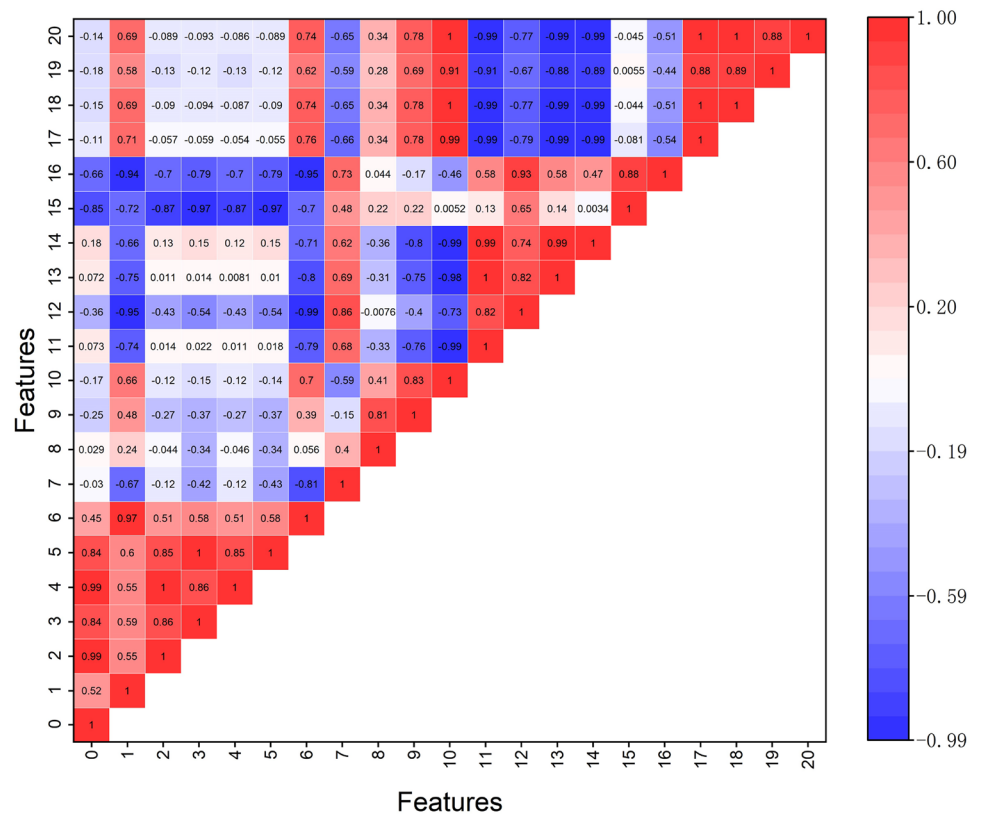
The AM-RCNN adopts a four-convolutional-layer architecture with batch normalization layers and activation functions incorporated throughout the network to enhance performance. It integrates several key components,

including a residual mapping module for feature transformation, an anti-noise (AN) processing unit for signal enhancement, and a GAP layer for feature aggregation.

The subsequent layers include a tensor-flattening operation for dimensionality reduction, a dropout regularization layer to mitigate overfitting [57], and a fully connected transformation layer for feature classification. The network employs a softmax activation function for final classification decisions, while utilizing parametric ReLUs (PReLU) throughout the model to improve feature representation learning [58]. The shortcut connection in the residual architecture from Layers 3 to 14 is automatically adapted to either identity mapping or a convolutional layer to maintain dimensional consistency with the main network structure. The AN processing module spanning network layers 9–14 is described in detail in Sect. 2.3 and illustrated in Fig. 2.

Table 3 Monitoring parameters of the MSR

Monitoring parameter	Unit
0-Reactivity	\$
1-Reactor power	MW
2-Fuel circulating pump speed (FCPS)	rpm
3-Coolant circulating pump speed (CCPS)	rpm
4-Fuel salt mass flow rate (FSMFR)	kg/s
5-Coolant salt mass flow rate (CSMFR)	kg/s
6-Air mass flow rate of the molten salt-air heat exchanger (AMFR)	kg/s
7-Core inlet temperature (CIT)	°C
8-Middle core temperature (MCT)	°C
9-Core outlet temperature (COT)	°C
10-Upper plenum temperature (UPT)	°C
11-Tube side inlet temperature of the primary heat exchanger (TITHE)	°C
12-Tube side outlet temperature of the primary heat exchanger (TOTHE)	°C
13-Tube side inlet temperature of the molten salt-air heat exchanger (TITSHE)	°C
14-Tube side outlet temperature of the molten salt-air heat exchanger (TOTSHE)	°C
15-Air side inlet temperature of the molten salt-air heat exchanger (AITSHE)	°C
16-Air side outlet temperature of the molten salt-air heat exchanger (AOTSHE)	°C
17-Power of PRVACS	kW
18-Air mass flow rate of the PRVACS	kg/s
19-Air inlet temperature of PRVACS	°C
20-Air outlet temperature of PRVACS	°C

Fig. 7 (Color online) The Pearson correlation analysis of the monitoring parameters in data set

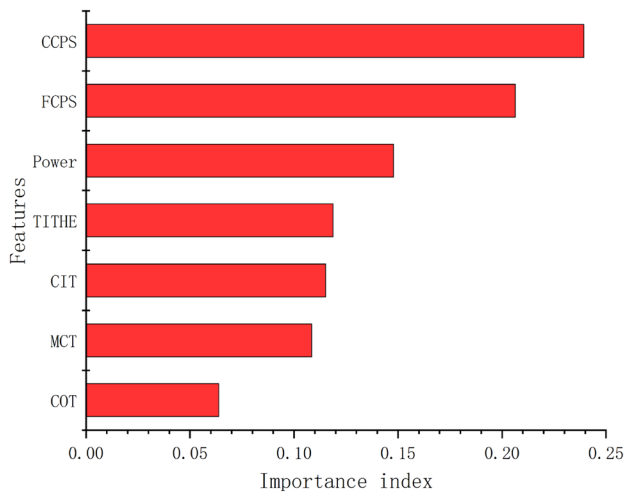


Fig. 8 (Color online) The evaluation and ranking of feature importance

Table 4 Architectural specifications of the proposed AM-RCNN framework

Layer number	Layer type		
1	Input		
2	Convolution		
3	Shortcut	BN	
4		PReLU	
5		Convolution	
6		BN	
7		PReLU	
8		Convolution	
9		AN module	GAP
10			Linear
11			BN
12			PReLU
13			Linear
14			Sigmoid
15	BN		
16	PReLU		
17	Convolution		
18	GAP		
19	Flatten		
20	Dropout		
21	Linear		
22	Softmax		

3.5 Evaluation index

Model performance was evaluated using confusion matrices [59], which provide a detailed analysis of classification performance. As illustrated in Fig. 10, the matrix structure for multiclass problems assigns distinct labels to each

category, with diagonal elements indicating correct predictions. The row sums correspond to the number of samples belonging to each actual class.

In addition, the evaluation incorporated accuracy and the F1-score metric. Classification accuracy is a fundamental performance indicator that quantifies the ratio of correctly predicted instances to the total number of samples. The F1-score represents the harmonic mean of precision and recall and is particularly sensitive to the lower value between these two measures. Higher F1-scores indicate improved model performance, especially in handling imbalanced classification tasks. Detailed definitions of precision, recall, F1-score, and diagnostic accuracy are provided in Eqs. (10)–(13) [60].

$$\text{Precision} = \frac{TP}{TP + FP} \times 100\% \quad (10)$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100\% \quad (11)$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% \quad (12)$$

$$\text{Diagnosis accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \times 100\% \quad (13)$$

where TP (true positive) and TN (true negative) represent the numbers of correctly classified positive and negative instances, respectively, while FP (false positive) and FN (false negative) represent the numbers of incorrectly classified negative and positive instances.

4 Results and discussion

4.1 Model performance and comparison

The case study primarily evaluated the proposed AM-RCNN against conventional CNN and RCNN architectures, focusing on comparative training and testing performance within similar network frameworks.

Figure 9 illustrates the architectural differences among the baseline CNN, standard RCNN, and the proposed AM-RCNN approach. To ensure consistency, the number of convolutional layers in both the RCNN and CNN models was fixed at four, matching that of the AM-RCNN. In addition, the other layers in the main structures of the RCNN and CNN were identical to those of the AM-RCNN. The shortcut structure in the RCNN was configured as identity mapping.

The training procedure employed cross-entropy as the optimization objective function. Model parameter optimization was performed using stochastic gradient descent

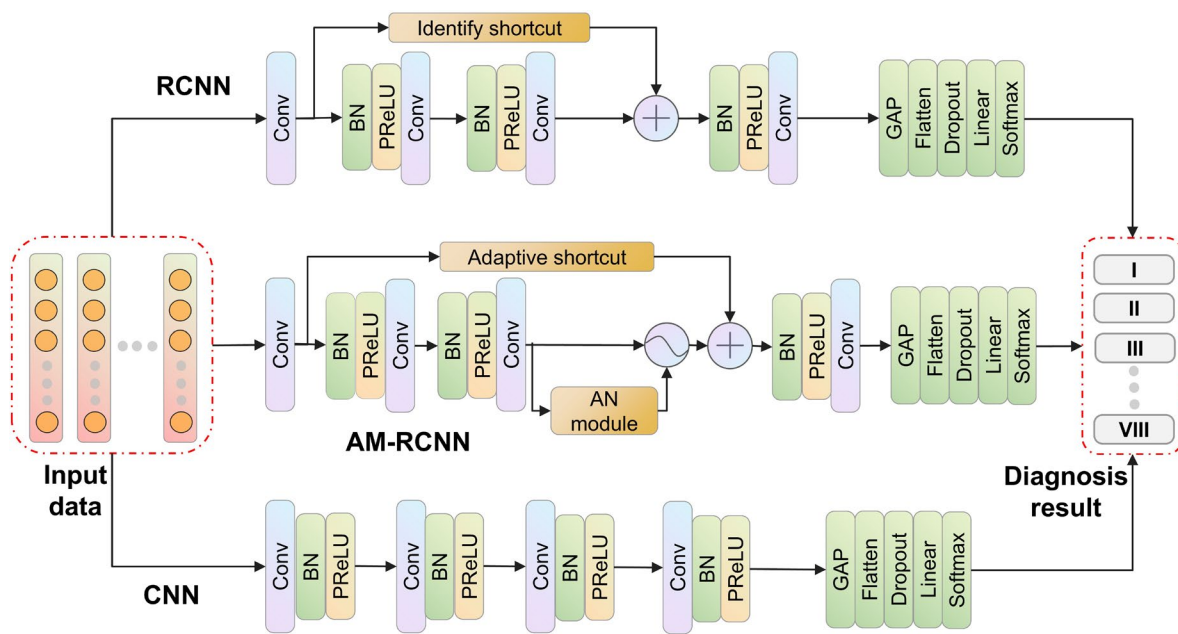


Fig. 9 (Color online) Architectural comparison of CNN, RCNN, and the proposed AM-RCNN

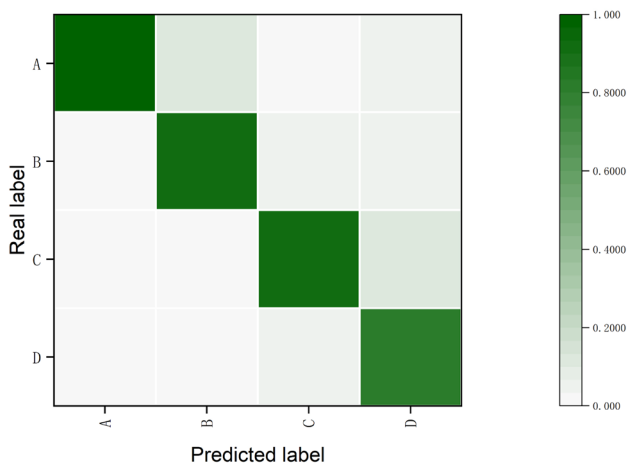


Fig. 10 (Color online) The classification performance matrix for multi-class prediction analysis

(SGD) with momentum acceleration and L2 regularization. The convolutional and fully connected layers were initialized using Kaiming and Xavier initialization methods [61, 62], respectively. Based on prior training experience, the model hyperparameters were configured as follows: a learning rate of 0.005 for gradient updates, a dropout probability of 0.5 for regularization, a mini-batch size of 128 samples per iteration, and 200 training epochs.

To prevent overfitting and determine the optimal model configuration, an early stopping strategy was adopted. The validation loss function served as the primary convergence

criterion, triggering early termination when no improvement was observed over ten consecutive training epochs. In such cases, the model parameters corresponding to the minimum validation loss, typically occurring ten epochs prior to termination, were retained as the optimal configuration.

Figure 11 presents the epoch-wise progression of training loss and validation accuracy across the different models, revealing several key observations.

- (1) According to the training loss curves, the proposed AM-RCNN model converged faster than the RCNN and CNN models. This indicates that the AM-RCNN model exhibits enhanced generalization capability and operational robustness, making it particularly suitable for deployment in noisy environments and transfer-learning scenarios.
- (2) The proposed AM-RCNN model triggered early stopping at the 28th epoch, compared with the 62nd epoch for RCNN and the 90th epoch for CNN. This demonstrates that the AM-RCNN model has stronger learning capability and stability, reducing training time and computational cost and making it suitable for flexible or real-time application environments.
- (3) All three models achieved high validation accuracy, exceeding 90%. Specifically, the validation accuracy of the proposed AM-RCNN model exceeded 95%, reaching 97%, while the RCNN achieved 95% and the CNN reached 94%.

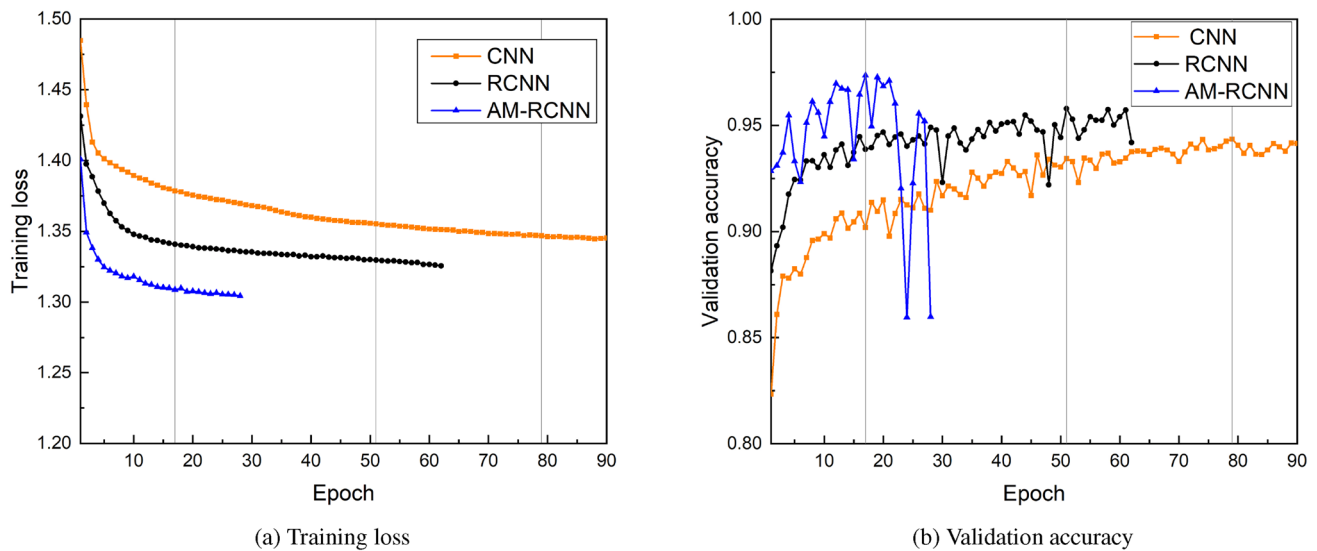


Fig. 11 (Color online) Training loss and validation accuracy trends across model architectures versus training epochs

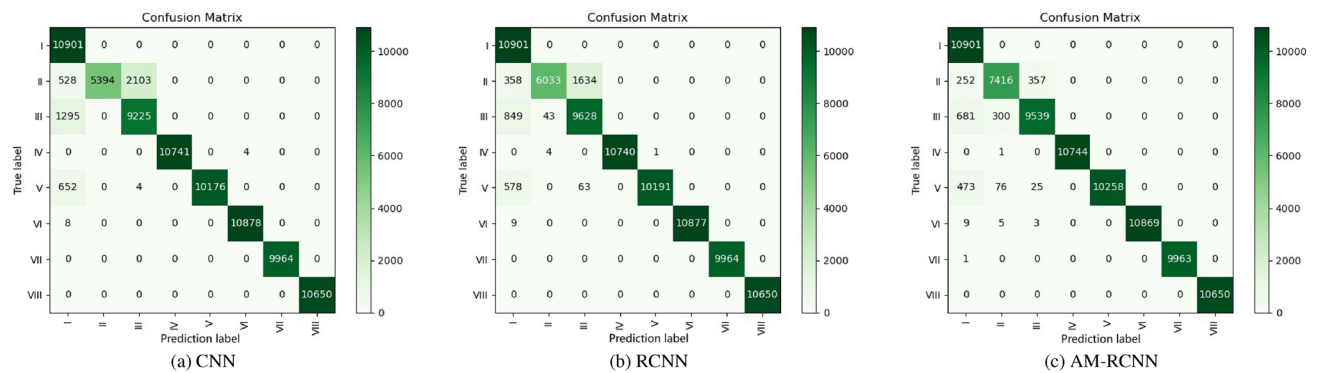


Fig. 12 (Color online) Test data classification performance comparison using confusion matrices

Table 5 Comparative evaluation metrics (accuracy and F1-score) on test dataset

Operation scenario		CNN	RCNN	AM-RCNN
F1-score (%)	I (normal)	89.8	92.4	93.9
	II (accident)	80.4	85.5	93.7
	III (accident)	84.7	88.1	93.3
	IV (accident)	100	100	100
	V (accident)	96.9	97.0	97.3
	VI (accident)	99.9	100	100
	VII (accident)	100	100	100
	VIII (accident)	100	100	100
Average F1-score (%)		93.9	95.4	97.2
Accuracy (%)		94.4	95.7	97.3

Figure 12 and Table 5 present the classification results for all evaluated models on the test dataset, including the confusion matrices and performance metrics (accuracy and F1-score). This analysis yielded several significant findings.

- (1) The accuracy of the AM-RCNN model on the test set is consistent with that on the validation set, further demonstrating the model's generalization capability.
- (2) Analysis of the true positive and true negative rates in the confusion matrices indicates accurate identification of all operational scenarios across all models. These findings demonstrate precise identification of critical system parameters associated with different operational scenarios. Comparative analysis revealed mean F1-scores of 93.9% for conventional CNN architectures, 95.4% for standard RCNN implementations, and 97.2% for the proposed AM-RCNN framework.

- (3) The relatively lower F1-scores observed for accident II, accident III, and steady-state conditions can be attributed to the inherent difficulty of distinguishing scenarios with overlapping feature distributions during certain operational phases. Specifically, accidents II and III, both reactivity insertion accidents, share the same triggering mechanism and exhibit similar development trends, making accurate classification particularly challenging. Similarly, certain transient accident conditions were misclassified as steady-state conditions because the dynamic evolution of key parameters during the early stages of accidents often resembles steady-state behavior.
- (4) The proposed model demonstrates superior performance in differentiating accidents II and III compared with conventional CNN and RCNN architectures, reflecting enhanced feature extraction and pattern-recognition capabilities.

4.2 Robustness test

Liquid-fueled MSR operational environments inherently contain multiple noise sources that affect detector readings, necessitating a rigorous evaluation of the robustness of the diagnostic model.

Real-world operational conditions typically exhibit composite noise characteristics arising from multiple sources. For analytical purposes, the mixed noise was approximated as Gaussian white noise. The noise impact was quantified using the signal-to-noise ratio (SNR), which evaluates the relative strength between the target signal and background interference. The SNR is mathematically defined as follows [63]:

$$\text{SNR(dB)} = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right), \quad (14)$$

where P_{signal} represents the spectral energy of the target signal component and P_{noise} denotes the corresponding noise energy within the measurement bandwidth.

Monitoring signals in NPPs generally maintain relatively low noise levels, with vibration measurements typically exceeding 30 dB SNR [64]. This threshold was therefore used as the baseline for assessing model robustness, and the corresponding test results are presented in Fig. 13 and Table 6. The results indicate that all three models performed well in noisy environments, achieving diagnostic accuracy exceeding 90%. In particular, the accuracy and F1-score of the proposed model remained close to 97%.

As shown in Fig. 14, the performance of all three models decreased in noisy environments, with the conventional CNN model experiencing the most significant decline. Performance evaluation under noisy conditions revealed reductions of 2.4% in classification accuracy and 2.6% in the F1 metric for the conventional CNN architecture. Similarly, the standard RCNN implementation exhibited an equivalent decrease of 2.4% in both performance metrics. In contrast, the proposed AM-RCNN framework demonstrated superior noise resilience, with only a 0.4% reduction in both metrics. This result highlights the effectiveness of the integrated anti-noise processing module in maintaining model stability.

4.3 Model optimization

To further enhance the performance of the AM-RCNN model, hyperparameter optimization was conducted using the BO method. In training deep neural networks, the learning rate, batch size, and dropout rate are critical hyperparameters that significantly influence learning efficiency, convergence speed, and model generalization capability. Consequently, these hyperparameters were selected as the primary optimization variables in this study.

The hyperparameter search space was defined as follows: the learning rate ranged from 1×10^{-4} to 1×10^{-1} ; the batch

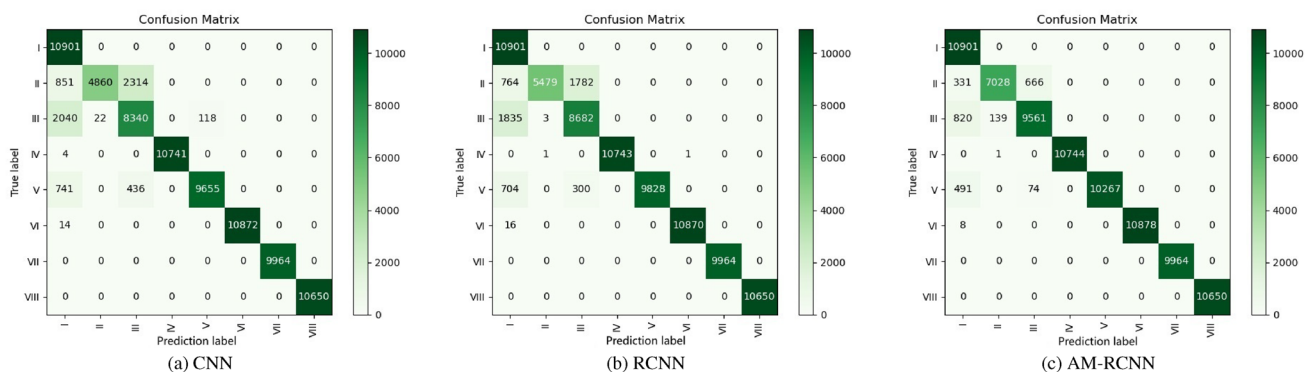


Fig. 13 (Color online) Test data classification performance under noisy conditions comparison using confusion matrices

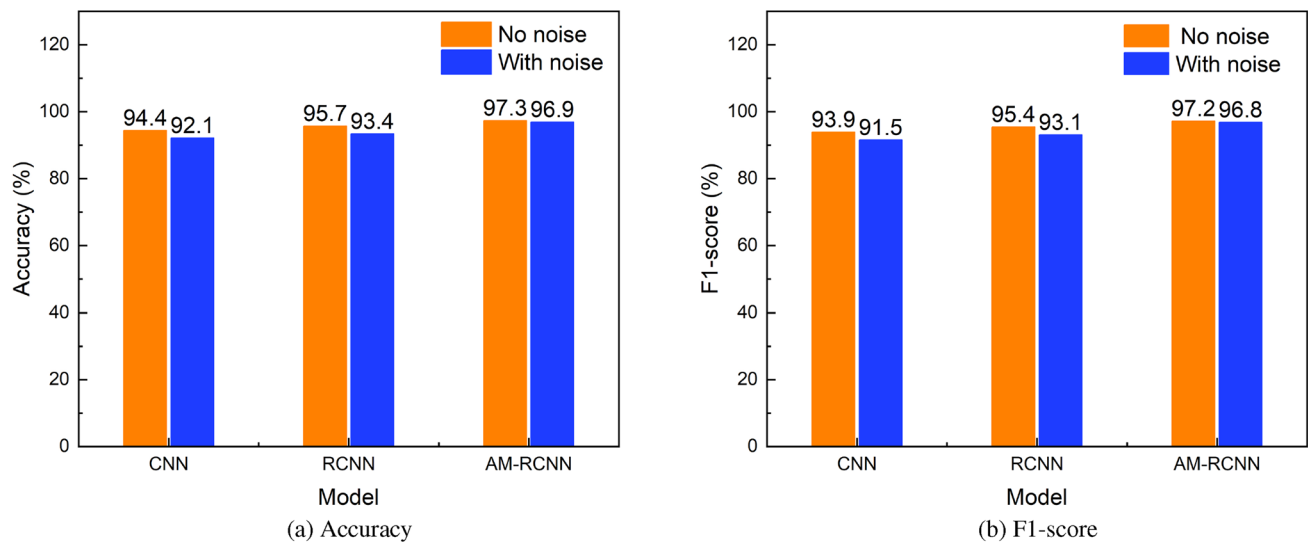


Fig. 14 (Color online) Comparison of different model results between noiseless data and noisy data

Table 6 Comparative evaluation metrics (accuracy and F1-score) on test dataset under noisy conditions

Operation scenario		CNN	RCNN	AM-RCNN
F1-score (%)	I (normal)	85.7	86.8	93.0
	II (accident)	75.3	81.1	92.5
	III (accident)	77.2	81.6	91.8
	IV (accident)	100	100	100
	V (accident)	93.7	95.1	97.3
	VI (accident)	99.9	99.9	100
	VII (accident)	100	100	100
	VIII (accident)	100	100	100
Average F1-score (%)		91.5	93.1	96.8
Accuracy (%)		92.1	93.4	96.9

size was randomly selected from the discrete set {32, 64, 128, 256}; and the dropout rate ranged from 0.1 to 0.6.

Figure 15 presents the results of the BO for diagnostic performance. The optimized configuration achieved 98.3% accuracy, representing a 1% improvement over the baseline model, with the following optimal parameters: a learning rate of 0.0003, a batch size of 256, and a dropout rate of 0.28.

5 Conclusions

To satisfy the safety and reliability requirements of advanced nuclear energy systems and reduce excessive manual intervention during operation, research on intelligent accident diagnosis systems is crucial for the future development of MSRs. This paper proposes AM-RCNN with an anti-noise

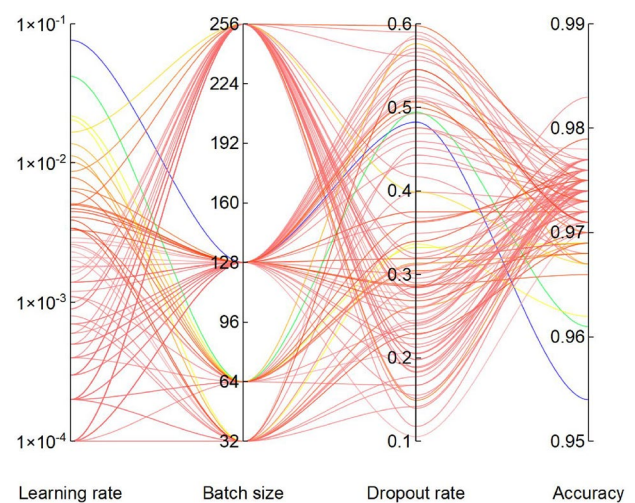


Fig. 15 (Color online) Hyperparameters optimization results of proposed AM-RCNN model

module and a parametric activation function and validates it using a designed MSR. The key contributions and distinctive features of the developed methodology are summarized as follows:

- (1) Rather than being limited to individual components or isolated subsystems, the selected input features comprehensively represent the operational state of the entire reactor system architecture. These parameters were systematically filtered for MSR accident diagnosis using Pearson correlation analysis and random forest importance ranking methods, thereby reducing data dimensionality and improving model efficiency.

- (2) Compared with traditional RCNN and CNN models, the proposed approach demonstrates improved diagnostic performance, particularly in noisy environments.
- (3) A BO framework was implemented for automated hyperparameter tuning, specifically targeting the learning rate, mini-batch size, and regularization parameters. This optimization strategy further improved the diagnostic performance of the AM-RCNN architecture, yielding a classification accuracy of over 98% when using the optimized model configuration.

The developed model provides real-time operational decision support for MSRs and has potential applications in other energy systems. Its architecture also offers a framework for developing deep learning-based diagnostic approaches.

Future research directions include: (1) advanced data preprocessing techniques, (2) heuristic optimization algorithms for model refinement, and (3) adaptive learning rate strategies to enhance training efficiency. Furthermore, sequential deep learning architectures, including LSTM networks and gated recurrent units, will be explored and integrated into a predictive analytics framework for MSR anomaly detection and early warning systems.

Author contributions All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Chao-Qun Wang. The first draft of the manuscript was written by Chao-Qun Wang, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The data that support the findings of this study are openly available in Science Data Bank at <https://cstr.cn/31253.11.sciencedb.j00186.00817> and <https://www.doi.org/10.57760/sciencedb.j00186.00817>.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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