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Fault prediction method for coalfields based on an SVD–ResCBAM–U-Net framework

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Abstract

Accurate fault prediction in coalfield seismic data is important for geological interpretation and the safe and efficient exploitation of coal resources. However, conventional fault interpretation methods and shallow machine-learning approaches usually rely on manually extracted seismic attributes. They often show limited robustness to noise and insufficient capability in characterizing fault continuity, boundary features, and small faults in structurally complex areas. To overcome these limitations, a fault prediction method based on the singular value decomposition–residual convolutional block attention module–U-Net (SVD–ResCBAM–U-Net) framework is proposed. First, SVD was used to denoise the seismic data and improve its quality. Then, residual blocks and a convolutional block attention module were incorporated into the U-Net architecture to enhance fault-related feature extraction and improve prediction performance. Experimental results show that the proposed SVD–ResCBAM–U-Net achieved the best performance among all compared models, with a global accuracy of 0.9556, a mean intersection over union of 0.6241, and a mean boundary F1-score of 0.6796. These results clearly demonstrate the proposed method's advantages in fault continuity, boundary delineation, and small-fault prediction, underscoring its effectiveness for fault prediction in coalfield seismic data under complex geological conditions.

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1. Introduction

Coal plays a critical role in the national energy security strategy. Safe and effective extraction is important for ensuring the safety of the national electricity supply and promoting sustainable economic growth.¹ Nevertheless, complicated geological formations, especially faults, often interrupt the continuity of coal seams. These structures are the primary geological factors that cause hazardous events, including water inrush^{2,3} and gas outbursts.^{4–6} Three-dimensional (3D) seismic technology has become the primary tool for detecting faults in coalfields due to its wide coverage and high detection accuracy.⁷ Faults usually appear as discontinuities, distortions, or abnormal

attenuation of seismic reflection events in seismic profiles.⁸ Manual profile-by-profile interpretation is not only time-consuming and labor-intensive but also prone to missing subtle responses associated with small faults. Technological advancements have advanced fault interpretation methods and led to a variety of seismic attributes based on discontinuity characteristics of reflected seismic events, including coherence,^{9,10} curvature,^{11,12} and variance,¹³ and more recently, hybrid discontinuity attributes.¹⁴ The methodologies have been enhanced, which has given birth to many wave features. However, human factors can lead to incorrect fault identification or omission. To reduce the influence of human bias, researchers have applied machine learning algorithms, including artificial neural networks,^{15,16} support vector machines,¹⁷⁻¹⁹ and random forests,²⁰⁻²² to build intelligent recognition models based on multi-attribute fusion. More recently, hybrid approaches that combine machine learning with seismic structural attributes have also been used to automate the extraction and mapping of complex fault systems.^{23,24} Although these methods have improved the efficiency and objectivity of fault interpretation, their performance still depends heavily on manually selected or constructed seismic attributes. Moreover, most methods rely on pointwise estimates and ignore the spatial distribution and structural patterns of faults. Therefore, when dealing with low-signal-to-noise geological data, attribute-based methods remain vulnerable to noise, making small faults difficult to identify.

Deep learning has made significant advances in seismic data processing and interpretation by enabling automatic feature extraction. It has been widely used in tasks such as seismic event detection,^{25,26} inversion,^{27,28} and fault recognition.²⁹⁻³¹ Xiong *et al.*³² trained a pixel-wise classification convolutional neural network using field seismic data and achieved automatic fault detection and mapping in seismic data cubes. Nevertheless, this sliding-window-based method is computationally expensive. To address this limitation, Wu *et al.*³³ presented a lightweight U-Net model for end-to-end fault segmentation on synthetic seismic records, demonstrating that fault identification can be formulated as a semantic segmentation problem. Since the introduction of U-Net by Ronneberger *et al.*³⁴ in 2015, researchers have continued to refine its architecture for more effective application to complex seismic data. For example, Yang *et al.*³⁵ proposed U-Net++, which improves the fusion of shallow and deep features through a dense connection strategy. Similarly, the WNet model proposed by Yan *et al.*³⁶ improves feature propagation between network layers by introducing an additional expansion path to the decoder. In addition, Cui *et al.*³⁷ introduced MS-U-Net to reduce spatial information loss during down-sampling by combining

multi-level encoder features through skip connections. To alleviate gradient vanishing during training, Gao *et al.*³⁸ integrated a residual learning mechanism into the U-Net architecture. Finally, to address the limitation of non-adaptive feature selection in the conventional U-Net, Sun *et al.*³⁹ incorporated attention mechanisms into the model, thereby improving the representation of fault features.

However, the use of attention mechanisms in U-Net alone cannot fully overcome noise interference in feature learning, nor can it completely address the gradient vanishing problem in deep network training for complex coalfield seismic data. Therefore, we propose a coalfield fault prediction method based on a singular value decomposition-residual convolutional block attention module-U-Net (SVD-ResCBAM-U-Net) framework. Previous studies have shown that SVD is effective in separating useful seismic signals from random noise.^{40,41} In this study, SVD is used during preprocessing to denoise the seismic data, thereby improving the signal-to-noise ratio of the network input by integrating residual blocks and the convolutional block attention module (CBAM) into the encoder. The model improves fault-feature extraction and enhances deep feature propagation. This strategy combines signal enhancement with network optimization and provides an effective solution for fault prediction in coalfield seismic data.

2. Denoising analysis of seismic profiles using singular value decomposition

2.1. Synthetic seismic data

To evaluate the effectiveness of SVD for seismic profile denoising, a fault-forward model was built to simulate noise characteristics observed in real seismic data. The model was designed to ensure that the simulated data closely resemble actual subsurface geologic conditions, as it was based on the characteristics of the roadway-exposed geological profiles. As shown in Figure 1, the model consists of seven layers arranged from top to bottom: the 1# sandstone layer, 1# coal seam, 2# sandstone layer, 2# coal seam, 3# sandstone layer, 3# coal seam, and 4# sandstone layer. The P-wave velocity and density of the sandstone layers were set to 3,000 m/s and 2.7 g/cm³, respectively, whereas those of the coal seams were set to 2,000 m/s and 1.5 g/cm³, respectively. To better reflect realistic seismic acquisition conditions, the trace spacing was set to 5 m, and the source wavelet was selected as a Ricker wavelet with a dominant frequency of 60 Hz.

To assess denoising performance across different noise levels, the synthetic data were contaminated with random noise at 20%, 50%, and 70%. The resulting seismic profiles are shown in Figure 2.

2.2. Principle of singular value decomposition-based noise attenuation

A two-dimensional (2D) seismic profile can also be represented by a data matrix X of size $m \times n$, where m is the number of time samples, and n is the number of seismic traces. After applying SVD to the matrix X , we obtain:

$$X = U\Sigma V^T = \sum_{i=1}^r \sigma_i u_i v_i^T \quad (1)$$

Here, the singular values satisfy, $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq 0$, where $r = \text{rank}(X)$. u_i and v_i denote the left and right singular vectors, respectively. Because seismic reflections usually exhibit strong lateral continuity, most of their energy is concentrated in a few leading singular values and their corresponding singular vectors. In contrast, random noise, which is incoherent in both space and time, tends to be distributed among smaller singular values corresponding to higher-order modes. The best rank- k approximation, according to the Eckart–Young theorem,⁴² can be constructed from the k largest singular values and their corresponding singular vectors as follows:

$$\hat{X}_k = \sum_{i=1}^k \sigma_i u_i v_i^T \quad (2)$$

where, $k \ll r$ represents the number of retained singular values, meaning that only the first k singular components contributing most to the total energy are used for seismic data reconstruction. This process preserves the main

seismic reflection signals while suppressing higher-order components to reduce the noise. In practice, k is usually selected based on the cumulative energy ratio or the inflection point of the singular value spectrum, such that:

$$\frac{\sum_{i=1}^k \sigma_i^2}{\sum_{i=1}^r \sigma_i^2} \geq \eta \quad (3)$$

where, η denotes a predefined energy threshold, typically set between 90% and 98% according to the requirements of seismic data processing.

2.3. Analysis of singular value decomposition denoising

To evaluate the effectiveness of SVD-based noise suppression, three groups of seismic profiles with varying noise levels were compared, as shown in Figure 2. The reconstruction rank of each dataset was determined using the energy-thresholding approach, with cumulative singular-value energy retention levels of 99%, 97%, and 90%, respectively. The seismic sections before and after SVD processing are shown in Figure 3.

The results show that SVD effectively suppresses background noise, resulting in smoother texture patterns in the seismic profiles. At a noise level of 20%, seismic responses near small faults are weak in the original profile, whereas event discontinuities become clearer after SVD processing. At a noise level of 50%, the reflection events

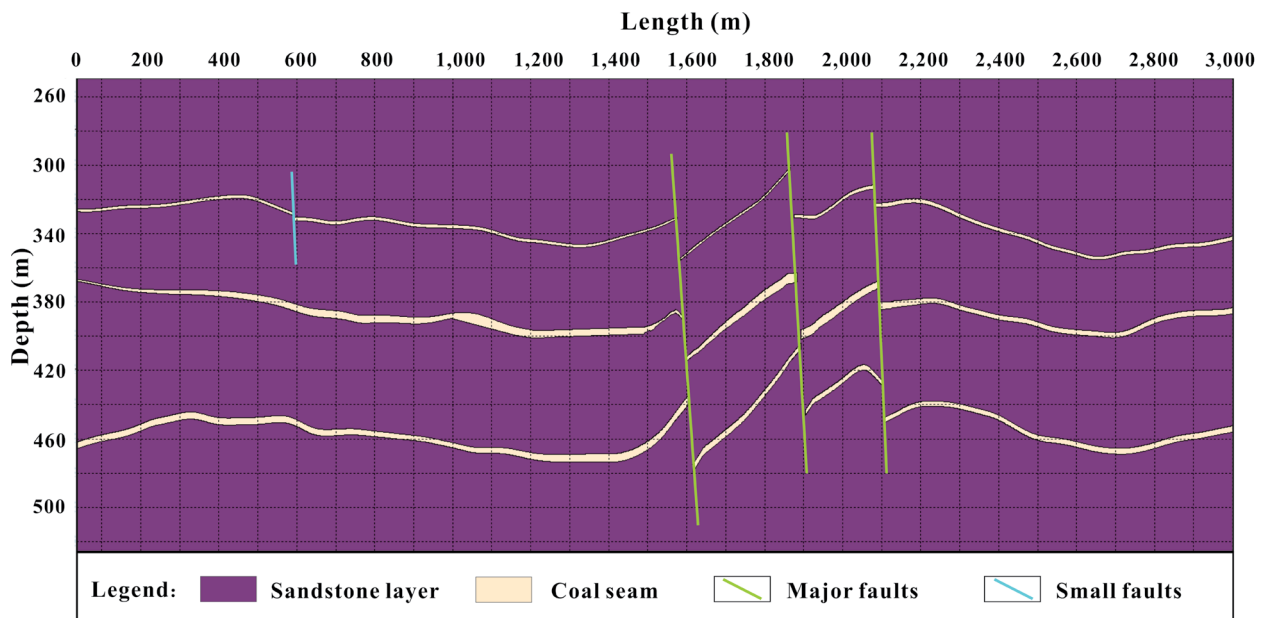


Figure 1. Seismic fault model with one small fault and three large faults

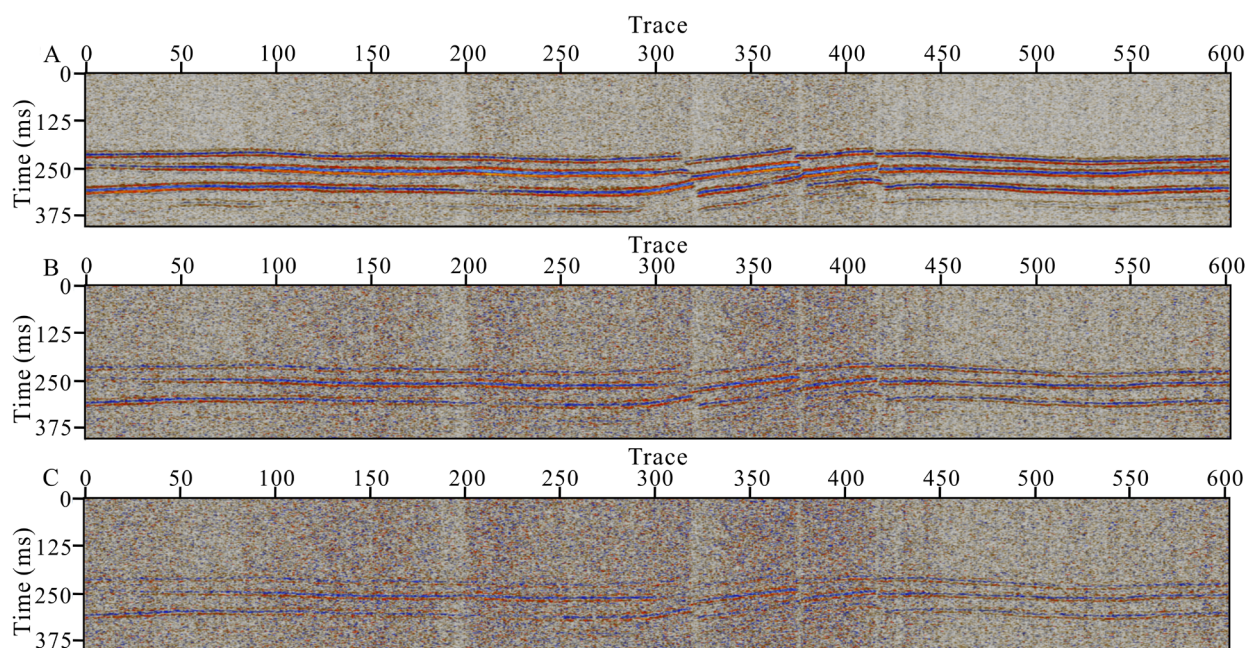


Figure 2. Noisy seismic profiles of the model under different noise levels: (A) seismic profile with 20% noise, (B) seismic profile with 50% noise, (C) seismic profile with 70% noise

become blurred in the original seismic profile. SVD processing significantly reduces random noise, clarifies seismic events, and better delineates the locations of large faults. Even at a noise level of 70%, SVD still preserves the main structural morphology, allowing seismic signals to remain distinguishable.

In summary, SVD shows stable denoising performance under different noise levels. It improves the quality of seismic images and provides a more reliable basis for subsequent analysis by suppressing random noise while preserving important reflection information.

3. Framework of the proposed singular value decomposition-residual convolutional block attention module-U-Net

The SVD-based denoising analysis of artificial seismic data indicates that this method can be successfully used to reduce noise and enhance phase and amplitude contrast, thus yielding high-SNR outputs in fault delineation. Since SVD is a dimensionality-reduction filter based on linear algebra, it cannot directly describe the spatial distribution and the complex geometric structure of fault systems. However, this paper presents the SVD-ResCBAM-U-Net framework, which integrates SVD preprocessing with deep learning algorithms and introduces attention mechanisms and residual structures. The overall workflow

of the proposed SVD-ResCBAM-U-Net fault prediction framework is shown in Figure 4. In this framework, data augmentation is first used to enlarge the sample space and enhance data diversity. After SVD denoising of the seismic profiles, the dataset was divided into training, validation, and test sets. The training set was used to train the ResCBAM-U-Net network, the validation set was used for model evaluation and hyperparameter tuning, and the test set was used to compare the prediction results with manual interpretation and to further examine the generalization capability of the proposed method.

3.1. Residual convolutional block attention module-U-Net network architecture

The proposed ResCBAM-U-Net is based on the classical U-Net architecture, a widely used fully convolutional network for semantic segmentation.⁴³ It adopts an encoder-decoder structure with skip connections, where the encoder extracts hierarchical features and the decoder progressively restores spatial resolution. The skip connections help fuse shallow and deep features, thereby improving pixel-level fault prediction.

In seismology, faults are usually expressed as reflector breaks or stratigraphic offsets. Seismic data often have a low signal-to-noise ratio and exhibit complex texture due to the complexity of the deep subsurface. Therefore, the seismic signature of small faults is often weak and can be easily obscured by noise. The conventional U-Net performs

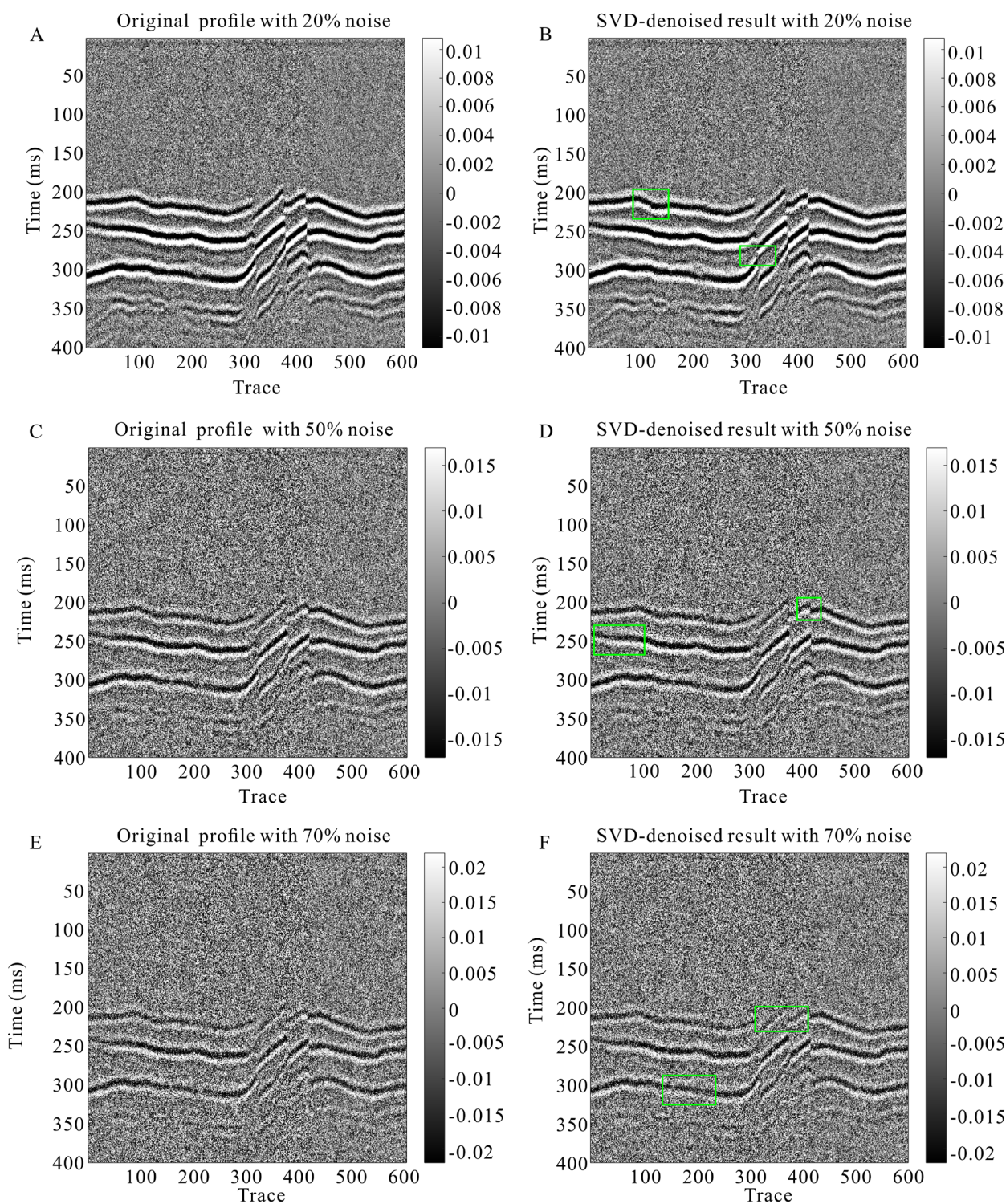


Figure 3. Comparison of seismic profile before and after singular value decomposition (SVD) denoising under different noise levels. For each noise level, the left panel shows the original noisy seismic profile and the right panel shows the corresponding SVD-denoised result. Specifically, (A) original profile with 20% random noise, (B) SVD-denoised result with 20% random noise, (C) original profile with 50% random noise, (D) SVD-denoised result with 50% random noise, (E) original profile with 70% random noise, and (F) SVD-denoised result with 70% random noise.

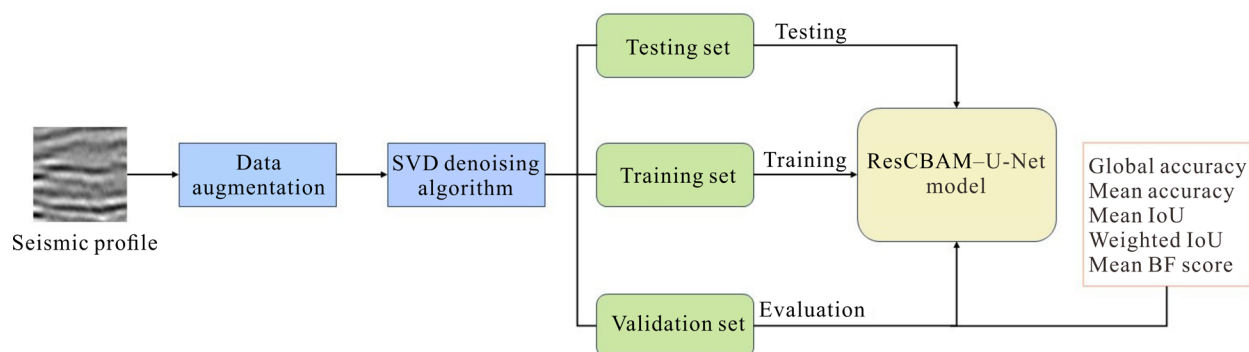


Figure 4. Framework of the singular value decomposition-residual convolutional block attention module-U-Net for fault identification
Abbreviations: BF: Boundary F1-score; IoU: Intersection over union; ResCBAM-U-Net: Residual convolutional block attention module-U-Net; SVD: Singular value decomposition.

convolutional operations without distinguishing between fault and background pixels. The lack of an adaptive feature-selection mechanism makes the model vulnerable to noise, resulting in false detections or discontinuous fault predictions. To capture global semantic information, the depth of the network needs to be increased, but standard U-Net models often suffer from gradient vanishing or feature degradation during deep training. Simple feature concatenations alone are insufficient to exploit the multi-scale residual information required to characterize complex geological structures. To address these limitations, this study proposes the ResCBAM-U-Net model (Figure 5). The U-Net encoder was enhanced by incorporating CBAM into the residual convolutional architecture. This design uses attention mechanisms to improve the learning of subtle fault signals, while residual connections help alleviate the gradient-vanishing problem. Together, these improvements promote stable convergence during deep network training.

3.2. Principle of the improved module

3.2.1. Residual learning mechanism

Deep network architectures are commonly used to represent the global semantic characteristics of faults in seismic data. Nevertheless, increasing network depth leads to repeated non-linear transformations. This phenomenon frequently causes gradient vanishing during backpropagation, which prevents effective parameter updating and optimization in deeper layers^{44,45}

To address gradient degradation, this study incorporates an additional residual learning module into the U-Net architecture. Unlike the direct mapping used in conventional networks, the residual structure introduces an identity shortcut connection. This mechanism allows the input to bypass the transformation layers and be added

elementwise to the output of the residual path. The final output of the residual unit can be mathematically expressed as follows:

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

where $F(x)$ denotes the residual mapping function in the proposed ResCBAM-U-Net architecture, which consists of convolutional layers combined with attention modules, and $\sigma(\cdot)$ denotes the rectified linear unit (ReLU) activation function. The residual connection unit is shown in Figure 6.

During backpropagation, the gradient of the loss function l with respect to the input x can be expressed as:

$$\frac{\partial l}{\partial x} = \frac{\partial l}{\partial H(x)} \cdot \frac{\partial H(x)}{\partial x} = \frac{\partial l}{\partial H(x)} \left(\frac{\partial F(x)}{\partial x} + 1 \right) \quad (5)$$

In this expression, the constant term 1 corresponds to the identity shortcut connection of the residual unit. This means that even when the gradient of the residual mapping function tends to 0, gradient information can still be directly propagated to shallower layers through this identity term. As a result, this mechanism helps alleviate the vanishing gradient problem during deep network training.

3.2.2. Convolutional block attention module-based feature enhancement mechanism

In coalfield seismic sections, continuous stratigraphic reflections and complex background noise typically appear as strong amplitude responses. In contrast, fault signals are typically characterized by small displacements or breaks in low-energy seismic events. Standard convolution operations treat all regions of an image equally and cannot

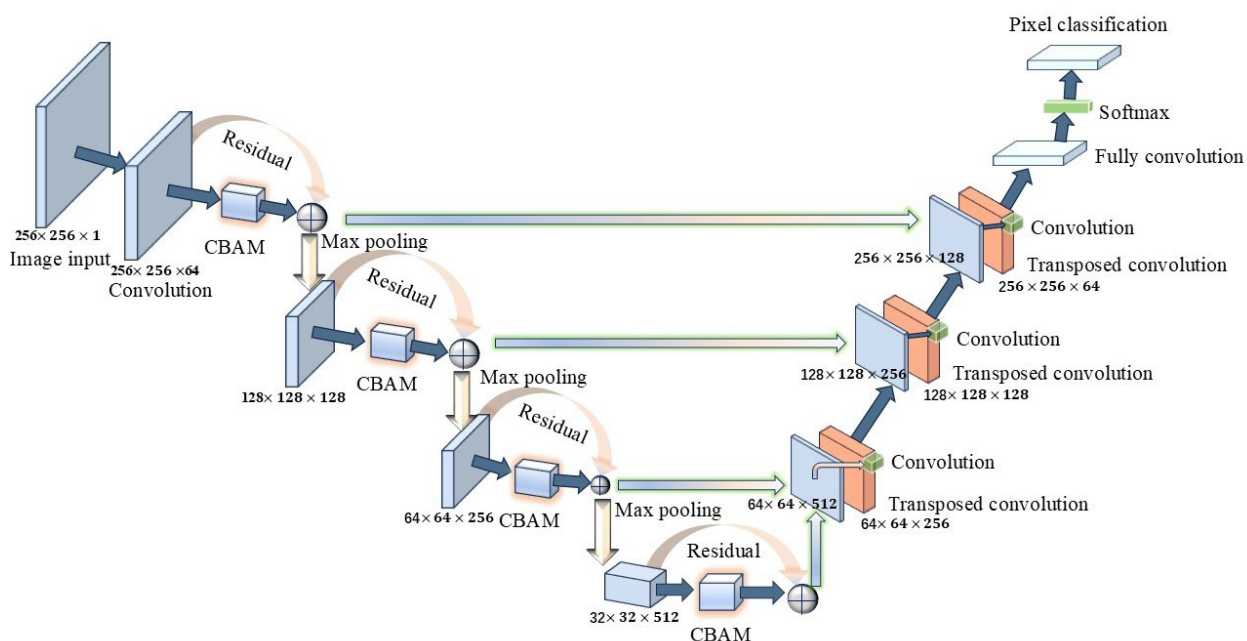


Figure 5. Architecture of the Residual convolutional block attention module-U-Net network
Abbreviation: CBAM: Convolutional block attention module.

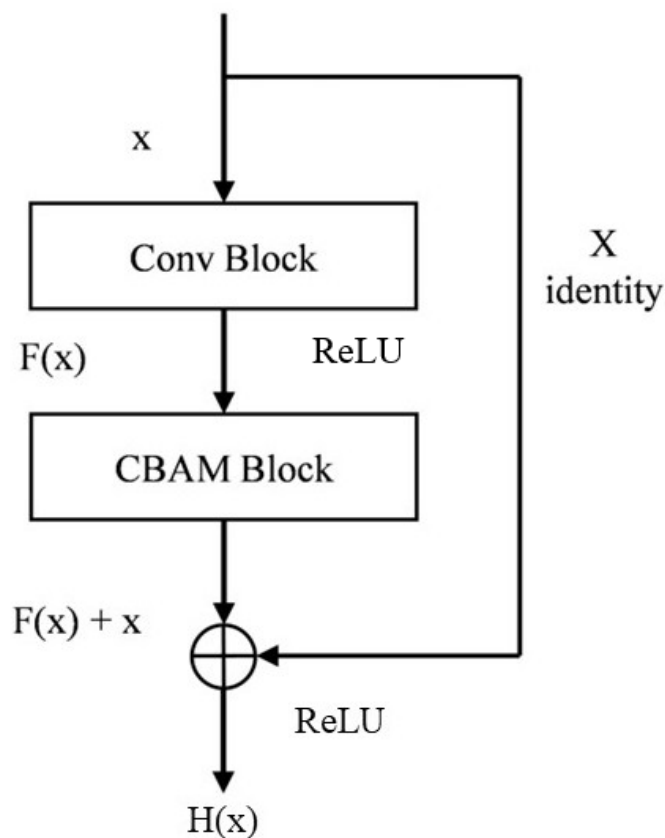


Figure 6. Residual connection unit

adaptively suppress background interference. Therefore, such subtle fault features can be easily obscured by high-energy reflectors.⁴⁶ To address this problem, the study introduces the CBAM into the U-Net decoder. This module improves the model's sensitivity to weak fault signals by recalibrating feature weights across both the channel and spatial dimensions.

As shown in Figure 7, CBAM consists of two submodules: the channel attention module and the spatial attention module. These two modules are connected in serial to enhance feature representation. The input feature is denoted as $F \in R^{C \times H \times W}$. F is first processed by the channel attention module to emphasize important feature channels, producing the intermediate feature F' . Then, F' is fed into the spatial attention module to locate fault structures in the spatial domain, yielding the final refined feature F'' .

The channel attention module performs global average pooling and global max pooling on the input feature map F in parallel. This operation aggregates spatial information to produce two complementary channel descriptors that capture global contextual information and local texture details, respectively. These descriptors are then fed into a shared multi-layer perceptron, followed by a sigmoid activation function to obtain the channel attention map $M_c(F)$. The resulting attention map is then used to multiply element-wise with input features, completing the first stage of feature recalibration in the channel dimension. This process can be formulated as follows:

$$M_c(F) = \sigma(\text{MLP}(\text{AvgPool}(F)) + \text{MLP}(\text{MaxPool}(F))) \quad (6)$$

$$F' = M_c(F) \otimes F \quad (7)$$

After the initial feature refinement by the channel attention module, the spatial attention module further localizes important features in the spatial domain. The channel-refined feature map F' is processed by average pooling and max pooling along the channel dimension, generating 2D spatial descriptors. These descriptors are concatenated and then convolved with a 7×7 kernel to integrate spatial information, followed by a sigmoid activation function to produce the spatial attention map $M_s(F')$. This map reflects the spatial distribution of fault-related features across the seismic profile. To obtain the final output feature, an element-wise product between $M_s(F')$ and F' is performed as follows:

$$M_s(F') = \sigma(f^{7 \times 7}([\text{AvgPool}(F'); \text{MaxPool}(F')])) \quad (8)$$

$$F'' = M_s(F') \otimes F' \quad (9)$$

Through these cascaded operations, the ResCBAM-U-Net architecture can suppress background noise and significantly enhance the representation of fault-zone features. Therefore, this approach improves the accuracy of fault prediction in complex geological settings.

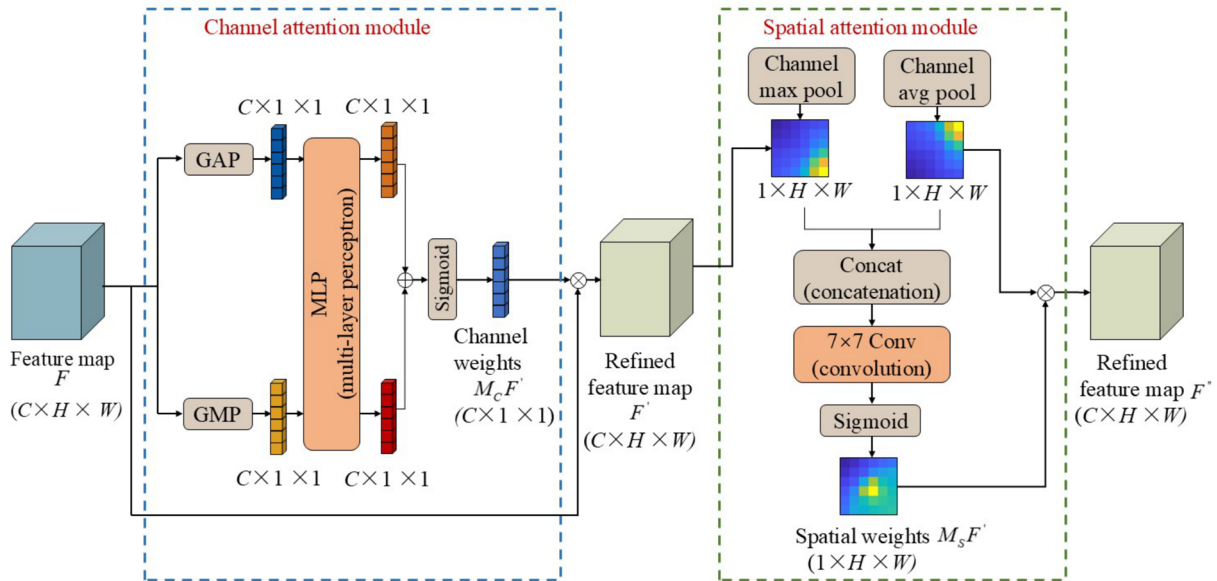


Figure 7. Schematic diagram of the convolutional block attention module structure
Abbreviations: GAP: Global average pooling; GMP: Global max pooling.

3.3. Evaluation metrics

In a field seismic profile, faults usually appear as linear features with complex morphology. In contrast to continuous stratigraphic reflections, faults occupy only a very small proportion of the pixels, leading to severe class imbalance. Therefore, this study uses a set of evaluation metrics to assess model performance. The first category introduces pixel-level metrics to evaluate the model's segmentation performance. These metrics include global accuracy (GA), mean accuracy (MA), mean intersection over union (MIOU), and weighted intersection over union (WIoU). The second category consists of the boundary F1 score, namely the mean BF-score, which is a boundary-distance-based metric used to evaluate the accuracy of fault-boundary extraction.

In this study, fault pixels are treated as positive samples, whereas non-fault areas are treated as negative samples. The corresponding confusion matrix is shown in Table 1. In this matrix, true positive denotes fault pixels correctly classified as faults; true negative denotes non-fault pixels correctly classified as non-fault; false positive denotes non-fault pixels incorrectly classified as faults; and false negative denotes fault pixels incorrectly classified as non-fault. GA is the ratio of correctly classified pixels to the total number of pixels. MA is calculated as the arithmetic mean of the class-wise accuracies and reflects the model's sensitivity to the minority class, namely faults. MIOU reflects the overlap between the predicted fault regions and the ground-truth labels, whereas WIoU evaluates the overall segmentation performance under class imbalance. The corresponding equations are given in Equations 10–13.

$$GA = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$MA = \frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right) \quad (11)$$

$$MIOU = \frac{1}{2} \left(\frac{TP}{TP + FN + FP} + \frac{TN}{TN + FP + FN} \right) \quad (12)$$

$$WIoU = \frac{TP + FN}{TP + TN + FP + FN} \cdot \frac{TP}{TP + FP + FN} + \frac{TN + FP}{TP + TN + FP + FN} \cdot \frac{TN}{TN + FN + FP} \quad (13)$$

The boundary F1 evaluates the accuracy of fault-boundary extraction on the matching of boundary pixels.⁴⁷ It can be formulated as follows:

$$Mean\ BF\ Score = \frac{2 \times P_b \times R_b}{P_b + R_b} \quad (14)$$

where, P_b represents the boundary precision, i.e., the proportion of predicted boundary pixels that are correctly aligned with the ground truth. Similarly, R_b denotes boundary recall, which is the proportion of ground-truth boundary pixels that are correctly identified. Pixel correspondence is determined using a predefined distance threshold.

Table 1. Confusion matrix for the fault identification

Class	Fault	Non-fault
Fault	True positive	False negative
Non-fault	False positive	True negative

4. Field data examples and analysis

4.1. Dataset construction

The seismic dataset used in this study was acquired from an operating coalfield in Henan province, China. The survey area is located at the southern margin of the North China Block, where tectonic activity is controlled by a thrust belt, resulting in a high density of faults with diverse morphologies. These structural features are mainly represented by nearly East–West-tending normal faults. The Carboniferous–Permian coal-bearing strata, particularly the No. 2 and No. 4 seams, show a significant acoustic impedance contrast with the surrounding roof and floor rocks, thereby generating strong seismic reflection interfaces. However, large thickness variations in the No. 2 coal seam, combined with local folding, cause highly disrupted seismic events near fault-break zones. Furthermore, compressive-torsional deformation in the southeastern part of the study area results in the superposition of minor faults, stratigraphic distortion, and diffraction interference. These complex geological conditions pose significant challenges for traditional structural interpretation.

The 3D seismic data volume used in this study consists of 641 inlines and 641 crosslines, with a 2-way travel time of 300–600ms. From this volume, 2D seismic profiles were extracted in the inline and crossline directions, resulting

in 256 seismic slices. The corresponding fault labels were generated from manual interpretation of the complete seismic profiles and then mapped onto the cropped samples to ensure a consistent input image size for the deep learning model. Representative examples of the fault prediction dataset are shown in Figure 8.

In the interpretation stage, it was noted that the number of fault samples is much lower than that of non-fault samples in the seismic profile, which can lead to class imbalance during model training. To counteract such influence, this paper proposes a data augmentation approach using geometric transformation. Some of the methods are: random rotations between $+5^\circ$ and -5° to simulate deviation angles caused by acquisition error and processing artifact; random horizontal inversion to increase the diversity of samples; random scaling with factors of 0.9–1.1 to mimic different spatial resolutions; and

random horizontal and vertical displacement by $+5$ and -5° , respectively, to simulate positional changes. During these augmentation operations, the corresponding fault-label images were transformed synchronously with the seismic images using the same parameters. This ensured pixel-level alignment between the seismic sections and labels. After these augmentation steps, a final dataset of 828 samples was formed. Out of this dataset, 76 samples were chosen at random as an independent test set to measure the generalization ability of the model. The other 752 samples were then divided into 676 training samples and 76 validation samples to enable training of models and hyperparameter optimization.

4.2. Network model construction

After data augmentation and dataset partitioning, a deep learning model for fault identification was constructed. First, the preprocessed seismic sections were denoised using

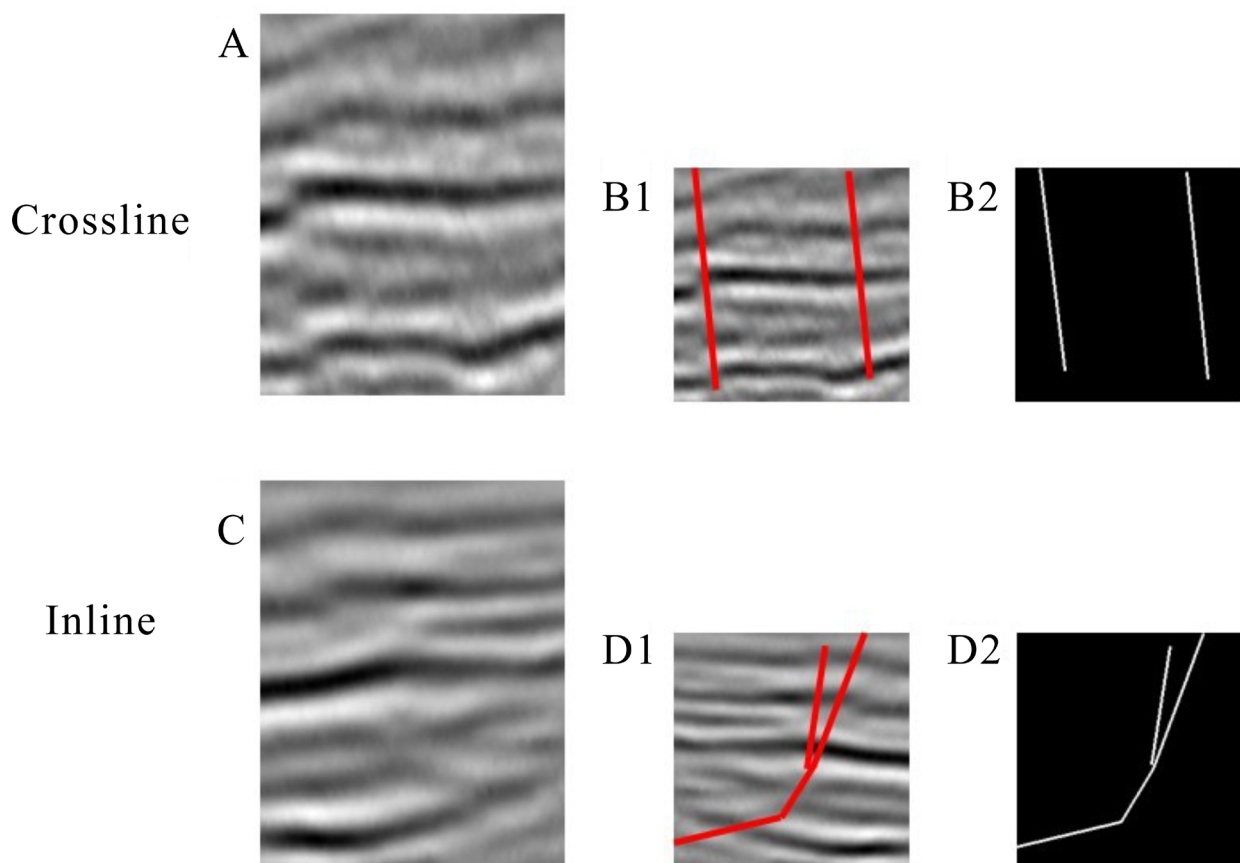


Figure 8. Schematic diagram of dataset construction for fault identification. (A) Original seismic profile in the crossline direction; (B1) cropped seismic image in the crossline direction with interpreted fault traces marked in red; (B2) corresponding fault label; (C) original seismic profile in the inline direction; (D1) cropped seismic image in the inline direction with interpreted fault traces marked in red; (D2) corresponding fault label. The fault labels were generated based on manual interpretation of the complete seismic profiles and then projected onto the cropped samples.

SVD. The economy-sized SVD was then used to decompose the seismic section matrix to achieve computational efficiency and stability in the denoising process, and the first r singular values along with their corresponding singular vectors were retained to obtain a low-rank approximation. We determined the reconstruction rank r for real seismic data using the cumulative singular-value energy criterion. The cumulative energy threshold was set to 90%, based on the SVD denoising analysis under different noise conditions presented in Section 2. This threshold helps reduce random noise. Meanwhile, effective seismic reflection information can be retained. The resulting seismic sections were normalized (amplitude scaled to the range of $[0, 1]$) and then fed into the ResCBAM-U-Net model.

After SVD denoising and normalization, the normalized seismic profiles were put into the ResCBAM-U-Net model to extract deep features and identify faults. In the training process, Adam optimizer was used to dynamically optimize the network parameters with an initial learning rate of 1.0×10^{-4} , a batch size of 16, and 200 training epochs. Each encoder stage in the network architecture has two convolutional layers. Linear convolutional features are normalized on a batch and processed by the ReLU activation function and then passed on to the CBAM attention module, where adaptive responses to features occur both in channels and spatially. The CBAM module output is then element-wise summed with the main-branch feature via a residual connection. The combination of features is max-pooled, decreasing the spatial resolution of the feature maps and reducing computational cost. Transposed convolution is used during decoding to gradually recover the spatial resolution of the feature maps. High-level features of the encoder at the same scale are connected with the current decoder features via skip connections to perform feature fusion. Following feature extraction, a convolutional layer is applied to the multi-channel features to produce a single-channel prediction map, and a sigmoid activation function is applied to obtain pixel-wise fault probabilities. To alleviate the class imbalance between fault and non-fault pixels in seismic profiles, a weighted binary cross-entropy loss function was adopted to quantify the discrepancy between predicted probabilities and ground-truth labels. The class weights were determined with reference to the pixel distribution in the dataset, where non-fault and fault pixels accounted for 97.34% and 2.66%, respectively. Accordingly, the weights for the fault and non-fault categories were set to 0.9 and 0.1, respectively. This was intended to enhance the learning of minority fault pixels while avoiding unstable training. As shown in Figure 9, training and validation losses decrease steadily with increasing number of epochs. The rate of

decline declines after about 50 epochs, and after about 100 epochs, the loss stabilizes near 0.1 and converges. The validation loss is consistently close to the training loss, and therefore, the suggested network successfully alleviates the problem of overfitting and has a good generalization capability.

The quantitative results on the validation set indicate a clear performance hierarchy among the compared models, and the proposed SVD-ResCBAM-U-Net achieves the best overall performance for fault prediction. As shown in Table 2, the proposed model attains the highest GA (0.9556), MA (0.8565), MioU (0.6241), WIoU (0.9386), and mean BF-Score (0.6796), indicating advantages in suppressing false detections, reducing missed fault response, preserving fault continuity, and improving boundary delineation. In addition, the confusion matrix of the proposed model (Figure 10) further confirms its reliable classification performance on fault and non-fault pixels. By contrast, the baseline U-Net performs the worst, with an MIOU of 0.5038 and a mean BF score of 0.4152, indicating strong background interference, poor structural continuity, and inadequate delineation of fault boundaries. Introducing SVD preprocessing improves U-Net performance. SVD-U-Net increases GA from 0.8883 to 0.9376 and mean BF-score from 0.4125 to 0.5504, showing that denoising helps suppress background noise. However, its MIOU remains limited at 0.5716, suggesting that denoising alone cannot fully compensate for the lack of effective fault-feature representation. ResCBAM-U-Net further improves the results by introducing residual learning and attention mechanisms, achieving a mean BF score of 0.6589 and an MIOU of 0.6090, which indicates stronger capability in boundary refinement and structural continuity modeling. To further evaluate the contribution of CBAM under SVD preprocessing, SVD-residual (Res)-U-Net was introduced as an ablation model. SVD-Res-U-Net also showed good performance, but its results were consistently lower than those of the proposed SVD-ResCBAM-U-Net across all evaluation metrics. This comparison demonstrates that integrating CBAM yields additional gains in fault-feature discrimination and boundary delineation. Overall, the combination of SVD denoising, residual learning, and attention enhancement enables the proposed model to achieve the most balanced and robust performance among all compared methods.

To summarize, SVD preprocessing and the feature-enhancement mechanisms in ResCBAM-U-Net work together effectively. Their integration reduces false detections and missed fault responses while improving fault localization, boundary delineation, and structural continuity.

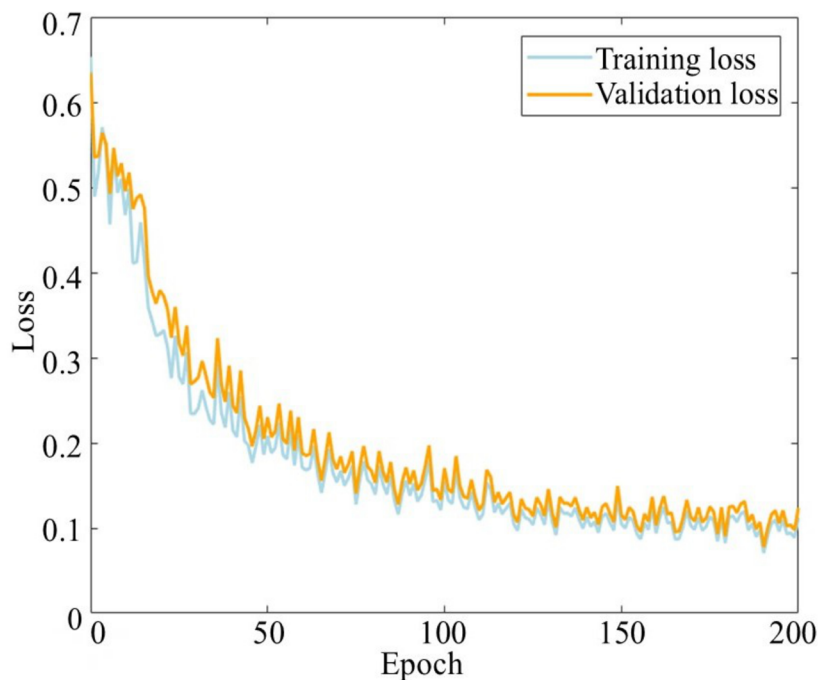


Figure 9. Loss curves of the training and validation set as a function of the number of epochs

		Predicted	
		Fault	Non-fault
Actual	Fault	0.7523	0.2477
	Non-fault	0.0393	0.9607

Figure 10. Normalized confusion matrix of the proposed Singular value decomposition-residual convolutional block attention module-U-Net model for fault and non-fault classification

4.3. Analysis of prediction results

The fault prediction results for representative samples from the test set in the study area are presented in Figure 11. Four representative cases were selected for visualization and comparative analysis. Figure 11A shows the original seismic profiles with manually interpreted fault traces marked in red. Figure 11B–F shows the prediction results of U-Net, SVD-U-Net, ResCBAM-U-Net, SVD-Res-U-Net, and the proposed SVD-ResCBAM-U-Net model, respectively. The prediction results of the proposed model are highly consistent with the manually interpreted fault traces in terms of fault contours, orientations, and geometric characteristics.

The prediction output of the proposed SVD-ResCBAM-U-Net model shows a significantly clean

background, structurally continuous fault shapes, and clear-cut boundaries between seismic profiles, as shown in Figure 11F. Adjacent faults in even intensely faulted areas or those that are structurally complicated still have a clear separation between them and do not falsely merge together. Moreover, regarding the location of small faults in the study area, the SVD-ResCBAM-U-Net model demonstrates strong detection capability; it can successfully locate these small features without compromising continuity. The baseline U-Net model (Figure 11B), on the other hand, predicts artificially expanded fault zones with bad structural continuity, and areas with minor faults are virtually absent from the response. With the addition of SVD preprocessing (Figure 11C), background interference in the prediction result is greatly reduced, and the fault responses become narrower than those of the U-Net

Table 2. Evaluation metrics of different models on the validation set

Model	GA	MA	MIoU	WIoU	Mean BF score
U-Net	0.8883	0.7731	0.5038	0.8685	0.4125
SVD-U-Net	0.9376	0.7974	0.5716	0.9183	0.5504
ResCBAM-U-Net	0.9497	0.8479	0.6090	0.9318	0.6598
SVD-Res-U-Net	0.9479	0.8487	0.6097	0.9217	0.61642
SVD-ResCBAM-U-Net	0.9556	0.8565	0.6241	0.9386	0.6796

Abbreviations: BF: BF: Boundary F1-score; GA: Global accuracy; MA: Mean accuracy; MioU: mean intersection over union; ResCBAM-U-Net: Residual convolutional block attention module-U-Net; SVD-U-Net: Singular value decomposition-U-Net; SVD-Res-U-Net: Singular value decomposition-residual-U-Net; SVD-ResCBAM-U-Net: Singular value decomposition-residual convolutional block attention module-U-Net; WIoU: Weighted intersection over union.

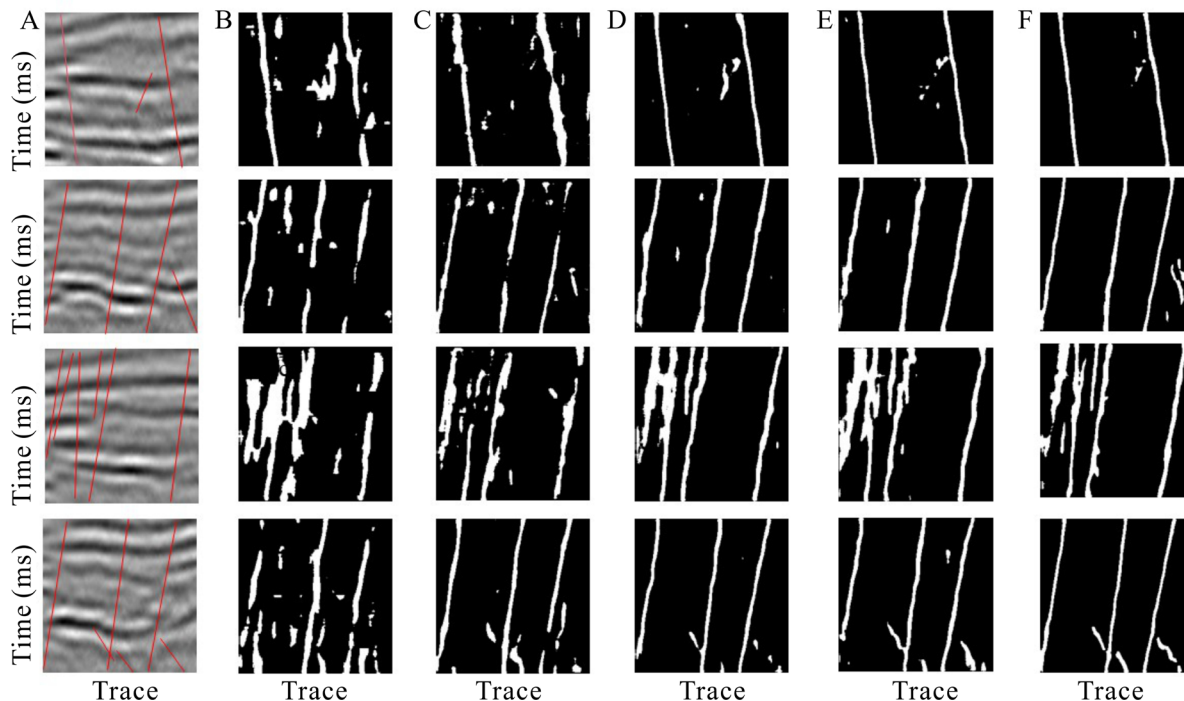


Figure 11. Comparison of fault prediction results on representative samples from the test set in the study area. (A) Original seismic profiles with manually interpreted fault traces marked by red lines; (B) prediction results of U-Net; (C) prediction results of SVD-U-Net; (D) prediction results of ResCBAM-U-Net; (E) prediction results of SVD-Res-U-Net, and (F) prediction results of the proposed SVD-ResCBAM-U-Net model. In the binary prediction maps, white indicates fault pixels and black indicates non-fault pixels.

model. Nevertheless, local fragmentation and missing segments remain visible, consistent with the overall validation performance reported in Table 2. In addition, the small faults predicted by SVD–U-Net mostly appear as scattered rather than coherent structural patterns.

The SVD–ResCBAM–U-Net model provides an absolute performance reference in seismic fault detection, going beyond the constraints of other architectures by using a highly integrated, two-step improvement approach. It is superior because of a specific functional synergy: whereas the SVD acts as a background filter, i.e., cleanses stochastic noise to reveal the major reflection plane, ResCBAM module functions as a refined architectural eye. Not only does the network map data, but the fusion of residual learning and dual-domain attention processes also actively strengthens the representation of weak fault signatures, which can easily be missed during regular processing. The new design is able to strike an unusual compromise between geological interpretation, which preserves the strict structural integrity of large-scale fault systems, and reduces the threshold for detecting the most obscure small faults by several orders of magnitude.

5. Conclusion

This study proposes an SVD–ResCBAM–U-Net framework for fault prediction by combining SVD-based denoising with an improved U-Net architecture. The effectiveness of the proposed method was verified using seismic data from a coal mine in Henan province, China. By introducing SVD during preprocessing, background noise in the seismic profiles was effectively suppressed, thereby improving the representation of fault-related seismic signals. In the network design, residual connections and CBAM were incorporated into the conventional U-Net framework. This design improves the extraction of discriminative deep features related to fault structures. The combination of SVD-based denoising, residual learning, and attention enhancement helps preserve fault continuity and produces clearer fault boundaries, especially in structurally complex or densely faulted areas. In particular, the proposed method shows clear advantages in detecting small faults and improves the structural consistency of the prediction results.

However, despite the effectiveness of the proposed SVD–ResCBAM–U-Net architecture in reducing false fault detections and improving the identification of small faults, some limitations still remain. First, the current study is based on 2D seismic sections and does not fully exploit the spatial continuity information in 3D seismic volumes. Thus, there is still room for improvement in characterizing 3D fault assemblages in complex structural areas. Second,

the model was mainly validated on an independent test set from the study area, and its generalization ability under different mining areas, geological conditions, and data qualities remains to be further assessed. Future work will extend the method to 3D seismic volumes and validate it using data from more mining areas.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Availability of data

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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