

# Optimal fault detection from seismic data using intelligent techniques: A comprehensive review of methods

Bhaktishree Nayak<sup>1\*</sup>, Pallavi Nayak<sup>2</sup>

<sup>1</sup> Government college of Engineering, Keonjhar At-Jamunalia Po-Old Townm Dist-Keonjhar Odisha 758001, India.

<sup>2</sup> Ravenshaw University, Cuttack Department of Geology, Ravenshaw University Cuttack Pin-753003, India.

**Abstract:** Seismic data plays a pivotal role in fault detection, offering critical insights into subsurface structures and seismic hazards. Understanding fault detection from seismic data is essential for mitigating seismic risks and guiding land-use plans. This paper presents a comprehensive review of existing methodologies for fault detection, focusing on the application of Machine Learning (ML) and Deep Learning (DL) techniques to enhance accuracy and efficiency. Various ML and DL approaches are analyzed with respect to fault segmentation, adaptive learning, and fault detection models. These techniques, benchmarked against established seismic datasets, reveal significant improvements over classical methods in terms of accuracy and computational efficiency. Additionally, this review highlights emerging trends, including hybrid model applications and the integration of real-time data processing for seismic fault detection. By providing a detailed comparative analysis of current methodologies, this review aims to guide future research and foster advancements in the effectiveness and reliability of seismic studies. Ultimately, the study seeks to bridge the gap between theoretical investigations and practical implementations in fault detection.

**Keywords:** Seismic data; Fault detection; Fault Segmentation; Machine learning; Deep learning; Adaptive learning

Received: 19 Aug 2024/ Accepted: 21 Mar 2025/ Published: 10 May 2025

## Introduction

Seismic data, obtained through seismic reflection and refraction methods, represent measurements of vibrations produced by controlled sources or natural phenomena within the Earth's interior. These data are indispensable across various industries. In oil and gas explorations, seismic data delineate subsurface structures, identify hydrocarbon-bearing traps or reservoirs, and optimize boreholes placement. In geology, they are instrumental in investigating Earth's structural features, including fault lines, stratigraphy, and tectonic movements - information critical for geological mapping and hazard assessment.

Additionally, seismic data play a pivotal role in environmental studies, such as underground water resource exploration, monitoring land subsidence, and assessing the geological impact of human activities, including mining and hydraulic fracturing. These diverse applications underscore the significance of seismic data as a powerful tool in scientific research, resource management, and risk mitigation across numerous disciplines (Ul Islam, 2020; Wang et al. 2023; Alfarhan et al. 2020).

This paper provides a comprehensive review of fault detection in seismic data interpretation, highlighting its pivotal role in understanding subsurface structures. The review focuses on recent advancements in automated and semi-automated fault detection techniques. Accurate fault detection enables geologists and engineers to delineate geological layers, fault lines, and stratigraphic sequences, which are critical for understanding geological evolution and identifying potential reservoirs. Furthermore, identifying fault lines is essential for mitigating hazards such as earthquakes and tsunamis, contributing to informed urban planning, infrastructure development, and

\*Corresponding author: Bhaktishree Nayak, E-mail address: [scholar.bhaktishreenayak@gmail.com](mailto:scholar.bhaktishreenayak@gmail.com)

DOI: 10.26599/JGSE.2025.9280049

Nayak B, Nayak P. 2025. Optimal fault detection from seismic data using intelligent techniques: A comprehensive review of methods. Journal of Groundwater Science and Engineering, 13(2): 193-205.

2305-7068/© 2025 Journal of Groundwater Science and Engineering Editorial Office This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0>)

disaster preparedness. In the oil and gas industry, effective fault detection enhances resource extraction strategies by revealing fault networks and structural complexities, facilitating more efficient drilling operations and reducing operational risks. Despite these benefits, fault detection from seismic data faces challenges such as noise, data ambiguity, and the massive volume of data. This review addresses these challenges while offering insights into current methodologies and future directions in the field (Aloisio et al. 2021; Share et al. 2019; Li and wang, 2021).

Seismic data is often affected by noise introduced by instrumentation, environmental factors, and geological heterogeneities. This noise can obscure fault signature or result in false detections. The interpretation of seismic images is further complicated by the inherent ambiguities of subsurface structures and the limitations of imaging techniques. Fault characteristics can vary widely due to factors such as lithology, fluid content, and tectonic settings, adding to the complexity of their identification.

Additionally, the vast volumes of data generated during exploration surveys necessitate efficient methods of processing and analysis to extract fault-related information. Traditional manual interpretation, while effective, is time-consuming and labor-intensive. Analyzing extensive datasets and complex geological formations requires skilled experts, often lead to delays in decision-making processes.

Recent advances in seismic fault interpretation involve the use of automated or semi-automated Machine Learning (ML) algorithms such as Random Forests (RFs), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs). Models like U-Net for image segmentation and Deep Fault Detection Networks significantly enhanced the accuracy and efficiency of fault detection. These techniques leverage large-scale data processing and advanced pattern recognition capabilities, reducing dependence on manual analysis and expediting decision-making process across various applications (Alfarhan et al. 2020; Hosseini-Fard et al. 2022; An et al. 2021; Mizutani et al. 2020).

Moreover, human interpretation of seismic data is influenced by the knowledge, experience, and subjective judgment of the individuals involved, making it prone to inconsistencies or incorrect fault identifications. Furthermore, the extensive amount of seismic data produced necessitates significant manpower, rendering manual interpretation economically unfeasible for large-scale

projects. To address these limitations, ML and DL algorithms have emerged as promising solutions, paving the way for automated fault detection in seismic data analysis.

When trained on labeled seismic datasets, ML algorithms excel at recognizing intricate patterns and correlations inherent in the data. These algorithms process vast amount of labelled seismic data, extract meaningful features, and identify subtle anomalies indicative of faults. Notably, their ability to generalize from learned patterns allow them to make accurate predictions on unseen data, thus enabling efficient fault detection.

DL models, particularly CNNs and RNNs, have demonstrated exceptional performance with large-scale seismic datasets. CNNs are highly effective at extracting spatial features from seismic images, making them ideal for detecting complex spatial patterns associated with faults. Conversely, RNNs are adept at capturing temporal dependencies in sequential data, which is critical for identifying faults in the temporal patterns of seismic signals. By leveraging these advanced DL architectures, seismic data analysts can navigate the complexities of large datasets to uncover critical, hidden features indicative of fault occurrences (Di et al. 2021; Michie et al. 2021; Bi et al. 2021; He et al. 2021). Despite significant advancements, existing fault detection techniques often lack comprehensive evaluation and analysis. While various methods have been proposed to address subsurface fault detection challenges, few studies provide a thorough summary of these approaches. This review paper aims to bridge this gap by contributing the following:

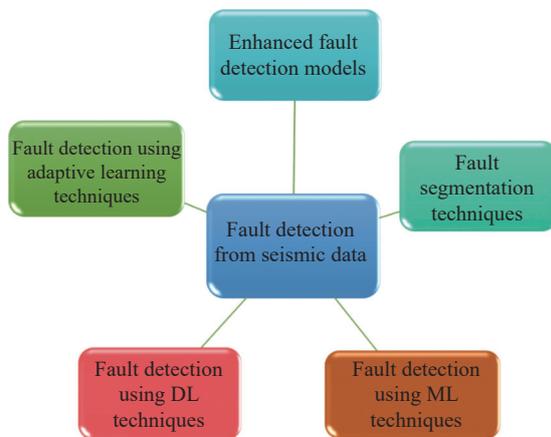
Enhancing fault detection from seismic data by reducing model complexity and training time, while incorporating physical and geological constraints. A detailed review of existing fault segmentation and ML techniques is provided, highlighting their significance and limitations.

Addressing label discrepancies, overfitting challenges, and reliability assessment issues by analyzing existing DL techniques, including adaptive learning and advanced fault detection models, with an emphasis on their significance and limitations.

Offering a comprehensive comparative analysis of the existing models, accompanied by a summary of findings and an exploration of future research directions based on these insights.

## 1 Review of fault detection from seismic data

Seismic surveys are the primary mechanism employed in the exploration of natural gas and oil, conducted both offshore and onshore. This process comprises two main stages: Data acquisition and seismic interpretation. A critical aspect of seismic surveys is fault detection, traditionally performed using reflection continuities, which are manually tracked in post-stack seismic data. This paper reviews fault detection methodologies from seismic data, focusing on identifying changes and discontinuities in subsurface structures. To ensure a comprehensive analysis, the review is structured across different directions and techniques. Fig. 1 illustrates the flow diagram of the review process for fault detection from seismic data.



**Fig. 1** Flow diagram of the review process for fault detection from seismic data

The process of fault detection from seismic data, as illustrated in Fig. 1, is carried out in five distinct directions. The review primarily focuses on fault segmentation, fault detection using ML techniques, fault detection using DL techniques, fault detection using Adaptive Learning techniques, and Enhanced fault detection techniques from seismic data.

### 1.1 Review of fault detection from seismic data using segmentation techniques

Fault segmentation from seismic data has been conducted using various techniques, with a focus on accuracy, scalability and efficiency. These methods differ in their architecture and techniques, but all aim to address challenges such as class imbalance, feature extraction, training complexity, and generalization to real-world data.

Wu et al. (2019) performed fault detection in seismic data using binary segmentation with Fully

Convolutional Networks (FCNs) trained on synthetic data. This approach utilized cross-entropy-based class-balanced loss to address the class imbalance, with 200 3D seismic images used to enhance scalability and efficiency. However, the method has limited practical applicability due to its reliance on manually labelled synthetic data. In contrast, Hu et al. (2020) improved the VGG16 architecture by incorporating Hybrid Dilation Convolution and Atrous Spatial Pyramid Pooling, which optimized training time and segmentation accuracy, though it still relies on a complex architecture. Dou et al. (2021) introduced an attention mechanism to enhance feature sensitivity, along with new loss functions,  $\Lambda$ -BCE and  $\Lambda$ -smooth L1, supervised on a few 2D seismic slices using a 3D CNN. Indeed, larger and more expansive training datasets often require more extensive synthetic data, as demonstrated by Lefevre et al. (2020), who used analog models to simulate fault growth experiments. Their work highlighted the need for more comprehensive synthetic training datasets. To improve edge detection capabilities, Dou et al. (2022) proposed the use of Mask Dice loss and multiscale compression-fusion blocks, which helped reduce false negatives in fault segmentation. However, their approach still depends on human annotations, raising concerns about the quality of the training data used.

The simulation of rupture rates along fault networks to advance seismic hazard assessment has been discussed by Visini et al. (2020), but issues related to accuracy persists. These issues were addressed by the FRESH and SUNFISH methodologies introduced by Li et al. (2023), which incorporates Fault-Seg-Net with multi-scale residual and attention modules. These approaches showed very high precision in detecting faults, particularly on synthetic datasets, but face scalability challenges when applied directly to large field datasets, as noted in other studies. To achieve high accuracy, Lima et al. (2024) proposed a DNFS segmentation model for data with sudden geological transitions, though it exhibits lower performance when dealing with gradual transitions. Liu et al. (2020) introduced a segmentation technique that embeds domain knowledge into CNNs, achieving better consistency in predictions and interpretability. However, it faces explainability issues, which were mitigated by introducing a multi-path learning-based dynamic and scalable network for fault detection. This network strikes a balance between precision and efficiency, but it requires continuous tuning to accommodate data variance. To improve parameter tuning, Khayer et al. (2023) proposed an innovative delineation strat-

egy, utilizing the Histogram of Oriented Gradients method for feature extraction, which enhances classification and generalization to real-world scenarios. Dou et al. (2024) proposed a semi-supervised FaultSSL framework that uses synthetic and limited labeled data. However, it remains highly dependent on sometimes inaccurate 2D slice annotations. Table 1 compares various fault segmentation techniques from seismic data, highlighting the advantages and disadvantages of algorithms such as Fault-Seg Net, Convolutional Neural Networks, Fully Convolutional Networks, and Deep Networks for Fault Segmentation.

## 1.2 Review of fault detection from seismic data using Machine Learning Algorithms

The application of Machine Learning techniques in fault detection from seismic data is discussed in this section. ML techniques are employed to analyze large datasets to identify faults. These techniques range from enhancing feature extraction and reducing noise to the precise localization of faults. While the use of ML algorithms in fault detection from seismic data offers several advantages, it also presents limitations that require

further advancements to overcome.

A fault diagnosis system utilizing SVM combined with VMD has been introduced by Zeng et al. (2021), focusing on noise reduction and feature extraction. This method outperforms PCA-based approaches, even in noisy environment, although it remains dependent on VMD, which requires a more robust noise-reduction technique. The finding is consistent with the report by Martín et al. (2023), where fault identification using K-Nearest Neighbors (KNN) was hindered by the geometrical complexity of faults in noisy spaces, making it difficult to establish fault boundaries. Ashraf et al. (2020) applied neural networks and geostatistical filtering to identify fracture networks, emphasizing the necessity of parameter optimization, and concluded that more complex tuning was required for further enhancement. Additionally, Noori et al. (2019) applied GPR technique for fault localization, but faced uncertainty issues, often resulting in false positives. To estimate fault risks, Ren et al. (2023) introduced a hybrid SVM with Particle Swarm Optimization model, which accurately detected faults, though it still experienced mispredictions in fault probability. Poor input data remains a common issue in such studies, as shown by Wu et al. (2021), who employed FCNs with cross-entropy loss functions for fault segmentation,

**Table 1** Comparison of fault segmentation techniques from seismic data

Reference	Techniques used	Significance	Limitations
Wu et al. (2019)	Fully Convolutional Neural Network	Efficient fault segmentation, Automatic feature extraction	Requires expert knowledge for accurate labelling, Time-consuming label creation
Hu et al. (2020)	CNN	Limited training set usage, Reduced training duration, Improved segmentation	Balancing model complexity with resources is challenging
Dou et al. (2021)	3D-CNN	Effective training with limited data, Attention mechanism for noise reduction	Hyperparameter tuning is required, Limited data for attention module
Lefevre et al. (2020)	Analog models	Understanding fault geometry determinants	Difficulty in achieving true scale similarity
Dou et al. (2022)	Fault-Net architecture	Reduction of false negatives, Preserving edge information	Incomplete labelling may lead to inaccurate training
Visini et al. (2020)	FRESH and SUNFISH	Improving PSHA methodologies	Lack of user-friendly interface, Uncertainty handling needs improvement
Li et al. (2023)	Fault-Seg-Net	High precision fault localization, Compound loss for uneven segmentation	Increased computational overhead, Training time prolongation
Lima et al. (2024)	DNFS	Enhanced accurate predictions	Sensitivity to geological transitions
Liu et al. (2020)	CNN	Improved interpretability, Better prediction accuracy	Need for deeper interpretability exploration, Additional domain knowledge integration
Li et al. (2024)	Fault-Seg-LNet	Achieve the tradeoff between model precision and efficiency	Continuous fine-tuning required, Adaptation to changing geological conditions
Khayer et al. (2023)	HOG	Enhances the accuracy of geological object delineation in seismic images	The quality of seismic data and the optimization of HOG parameters affects the system performance
Dou et al. (2024)	FaultSSL	Enhances fault detection by effectively integrating limited labelled data	Constrained by the reliance on sparse and potentially inaccurate 2D slice annotations

but faced limitations in integrating domain knowledge. In an attempt to improve detection efficiency, Wu et al. (2019) incorporated synthetic seismic images along with CNNs, although the method heavily relied on the trainability of CNNs for achieving optimal performances. Recently, Jang et al. (2023) used Random Forests (RF) in combination with PCA for fault distribution analysis, though they encountered challenges in interpreting feature importance.

Jang et al. (2023) and Gong et al. (2024) also recognized the need for advanced methods to manage feature interaction and temporal dynamics, respectively. Despite achieving better detection accuracy with machine learning models, they highlighted the challenge of correctly interpret the results. Wang et al. (2020) and Feng et al. (2022) introduced knowledge distillation and workflow-based Loc-FLOW within the framework of machine learning, to detect faults more efficiently. Both approaches focused on enhancing the training process but encountered difficulties with geological configurations, which made them hard to apply. These challenges were addressed by the tomography method proposed by Waheed et al.

(2021), which uses neural networks and physics-informed regularizers. All three studies underscore the importance of high-quality data and appropriate training strategies to minimize errors in fault detection models. Table 2 presents a summary of some ML algorithms used for fault detection in seismic data: Support Vector Machines, Convolutional Neural Networks, K-Nearest Neighbors, Random Forests, and Fully Convolutional Networks with Gaussian Process Regression.

### 1.3 Review of fault detection from seismic data using Deep Learning algorithms

The introduction of Deep Learning techniques has notably advanced fault detection in seismic data analysis, addressing both challenges and limitations in the field. For pixel-level binary classification of faults, An et al. (2021) employed Deep Convolutional Neural Networks (DCNNs), which reduced the dependency on labelled crosslines, thus improving performance compared to earlier methods. However, challenges related to labelling

**Table 2** Review of fault detection from seismic data using ML algorithms

Reference	Techniques used	Significance	Limitations
Zeng et al. (2021)	SVM, VMD	Intelligent fault diagnosis, noise attenuation, strong relationship between seismic features and faults	Ineffective for non-stationary or complex noise patterns
Martín et al. (2023)	KNN	Interactive 3D fault identification, lithological classification	Struggles with complex fault geometries and heterogeneities
Ashraf et al. (2020)	NN, ACO	Advanced fracture network recognition, fault identification using seismic data	Requires careful parameter tuning for optimization, may not effectively handle all types of faults
Noori et al. (2019)	Gaussian process regression	Fault detection via abnormality identification, fault edge determination	Propagation of uncertainties from GPR into fault detection may lead to false positives or missed detections
Ren et al. (2023)	SVM, PSO	Provided insights into fault exposure conditions for roads and wells in the target coal seam	Lack of true fault existence probability assessment.
Wu et al. (2021)	FCN	Fault segmentation based on FCN, balanced loss function for model optimization	Incorporating physical and geological constraints in model architecture is challenging
Wu et al. (2019)	MTL-CNN	Fault detection, structure-oriented smoothing, seismic normal vector estimation	Designing CNN architectures for improved structural interpretation is challenging
Jang et al. (2023)	PCA, RF	Relationship between fault distribution and controlling factors, efficient RF classification	Challenge in interpreting feature importance due to RF's bias toward correlated features
Gong et al. (2024)	SOM-GWO-SVM	Intelligent data preprocessing, fault identification accuracy improvement	Struggles to capture temporal dynamics of fault patterns and seismic activity evolution
Wang et al. (2020)	CNN	Enhanced fault detection through knowledge amalgamation, student CNN trained on synthetic and field data	Investigation of appropriate training data sets and labels needed for effective fault interpretation
Feng et al. (2022)	LOC-FLOW	Enhances earthquake catalog accuracy and provides high-resolution velocity structures	Effectiveness is constrained by the availability and quality of seismic data from dense station networks
Waheed et al. (2021)	PINNTOMO	Enhances seismic tomography by leveraging physics-informed neural networks	Has extremely complex geological settings

inconsistency remained a significant issue. To achieve comparable accuracy results, Palo et al. (2023) focused on Graph Convolutional Networks (GCNs), demonstrating their use in fault detection similar to traditional CNNs. While GCNs showed potential, the feature engineering process revealed limitations that require further improvements for better data representation. Meanwhile, an encoder-decoder network was proposed by Alfarhan et al. (2020) for fault detection and salt dome identification, leveraging transfer learning and residual blocks to overcome the issue of limited labelled samples. Despite these advancements, the model faced uncertainty estimation challenges, particularly under complex and uncertain conditions, emphasizing the need for further enhancement to ensure reliability in such scenarios.

Besides, Bi et al. (2021) proposed a volume-to-volume U-shaped neural network with attention mechanism, which exhibited highly accurate results but faced challenges with low dip-angle thrust faults. Li et al. (2019) modified a CNN-based semantic segmentation approach to work with relatively small training sets. However, they encountered class imbalance issues, which impeded performance; this was addressed by An et al. (2021), Alfarhan et al. (2020) and Xu et al. (2021) applied a 3D convolutional autoencoder to improve the extraction of spatial structure, with architecture tuning and hyperparameter optimization for better results.

Li et al. (2021) focused on improving the quality of fault maps through seismic image denoising and super-resolution using a CNN-based approach. This approach aligns with Wu et al. (2022), who used U-Net architecture for multi-scale fault imaging, but found it computationally impractical. To reduce the high training costs of 3D networks, Lin et al. (2022) proposed a 2.5D channel attention U-Net. This method faced overfitting and limited labelled data issues, illustrating the common trade-off between the need for large datasets and model efficiency found in many studies.

Ma et al. (2023) developed a multimodule elastic wave inversion model that performs well in noisy conditions, emphasizing the importance of model adaptability to different environments. This theme was further explored by Vu and Jardani (2022a and 2022b), who focused on fracture mapping and transmissivity/storativity assessments in heterogeneous aquifers. Their multitask CNN model demonstrated the benefits of shared learning mechanisms, but it also highlighted the need for further exploration into how variations in aquifer conditions can affect performance. Table 3 sum-

marizes some of the DL methods used in seismic data fault detection, including GCN, DCNN, U-Net, and Encoder-Decoder.

#### 1.4 Review of fault detection from seismic data using adaptive learning algorithms

A significant amount of research has focused on the use of adaptive learning algorithms for fault detection in seismic data. These approaches often emphasize methodologies like transfer learning and the utilization of synthetic data, addressing both their potential and limitations.

Zini et al. (2019) introduced SeisNet, a CNN featuring a unique "butterfly" architecture, designed to address the issue of limited seismic data. While the architecture demonstrated potential, it underscored the need for enhanced seismic data processing techniques. Similarly, Zhou et al. (2021) utilized transfer learning to adapt CNNs for seismic data analysis, leveraging pre-trained classifiers. Their method achieved high accuracy on synthetic North Sea datasets but struggled with achieving fine resolution of fault discontinuities in three-dimensional space. This limitation highlighted a recurring theme in fault detection: The gap between synthetic performance and practical applicability.

Cunha et al. (2020) explored key challenges associated with synthetic seismic data, such as noise disturbance and mismatches between seismic signal frequencies and fault distribution. They proposed a transfer learning approach to bridge the gap between synthetic and real seismic data, aiming to improve fault detection without relying heavily on labelled datasets. However, this method did not fully address noise challenges frequencies encountered in real-world seismic applications.

Ao et al. (2021) contributed to the debate with a seismic dip estimation transfer learning method that employs knowledge-driven sample augmentation. However, concerns remain regarding the reliability of traditional results compared to network predictions. Dou et al. (2024) introduced a Tiny Self-Attention mechanism inside an HRNet architecture to enhance seismic data representation and fault detection capabilities, though issues with sparse distance matching problems were reported. To address this, Zhou et al. (2021) proposed a progressive learning architecture that reduced some limitations of traditional deep learning models. However, the need for updates with changing datasets, which can introduce bias,

**Table 3** Review of fault detection from seismic data using DL algorithms

Reference	Techniques used	Significance	Limitations
An et al.(2021)	DCNN	Efficient fault recognition methodology outperforms state-of-the-art methods, anticipates small errors	Mitigating label discrepancies, reliable model training
Palo et al.(2023)	Graph Convolutional Network (GCN)	Interpreting faults in seismic data, good accuracy	Lacks feature engineering strategies
Alfarhan et al. (2020)	Encoder-decoder deep neural network	Good detection accuracy, robustness to labelled data scarcity	Lack of uncertainty estimation methods
Bi et al.(2021)	Volume-to-volume neural network	High prediction accuracy, low computing costs	Ineffective for low dip-angle thrust faults
Li et al.(2019)	U-Net	Efficient fault detection with small training sets, increased interpretation efficiency	Class imbalance leads to less accurate fault detection
Xu et al. (2021)	3D convolutional autoencoder	Handling seismic data directly, with good accuracy	Needs optimization of architecture and hyperparameters
Li et al. (2021)	Deep CNN	Enhanced perceived quality, better fault detection	Artifacts, slight overfitting
Wu et al. (2022)	Modified U-Net with dilated convolutions	Improved capacity for multi-scale information, better fault identification	Requires further computational optimization
Lin et al. (2022)	2.5D CAU-net with channel attention mechanism	Efficient utilization of correlation between seismic slices, enhanced fault detection	Model overfitting with a larger cropping approach
Ma et al. (2023)	U-Net and CNN	Accurate multiparameter elastic wave inversion, strong generalizability	Physical limitations, noisy data sensitivity
Vu and Jardani (2022a)	SegNet	Accurately map fracture networks in heterogeneous aquifers using hydraulic tomography data	Not fully capture the complexities of real-world fracture geometries and hydrological conditions
Vu and Jardani (2022b)	HT-XNET	Simultaneously reconstruct transmissivity and storability with improved accuracy	Need in-depth considering limits under variance of the method on aquifer conditions and data

underscores the necessity for more robust methodologies.

Wei et al. (2022) improved CNNs trained on imbalanced datasets using transfer learning but overlooked the importance of fine-tuning focal loss parameters. Similarly, Li et al. (2024) employed a multi-attribute fusion method to enhance detection process, yet faced challenges related to high computational overhead and inefficiency. Mustafa et al. (2024) focused on visual analysis of seismic fault annotations through an attention-guided training framework, improving prediction accuracy for both labelled and unlabelled faults. This aligns with broader trends in the literature, which increasingly emphasize incorporating cognitive processes into model training.

To address imbalanced seismic amplitude data, Zeng et al. (2024) proposed a 3D-UNet-based dual attention fault detection model, but its reliance on shallow features resulted in unsatisfactory outcomes. Zhang et al. (2022) introduced a two-stage deep transfer learning approach for hydraulic fracture imaging, enabling rapid data generation and accurate reconstructions, albeit with some approximation errors. Titos et al. (2023) applied transfer learning to volcano-tectonic earthquake monitoring, demonstrating the adaptability of their models to diverse seismic characteristics. However, they cautioned that the quality of the master dataset heavily influences performance.

Table 4 summarizes the adaptive learning algorithms used in seismic data fault detection, including transfer learning, SeisNet, U-Net-based domain-adversarial neural networks, DANN, self-attention, Fault-Attri-Attention, and 3D-UNet.

### 1.5 Review of enhanced fault detection models from seismic data

Recent studies on fault detection from seismic data have introduced numerous techniques, each with unique strengths and challenges. Enhanced hybrid and optimized methods have proven particularly effective in fault identification. Yan et al. (2019) proposed a forward and backward diffusion scheme based on PCA-planarity, which leverages fault image characteristics while suppressing irrelevant noise. However, it highlighted the need for more advanced algorithms tailored to geologically diverse environments. Similarly, Mousavi et al. (2022) employed morphological algorithms, such as erosion and edge detection, to minimize noise disturbances without compromising image quality. This approach successfully defined faults with high precision in 3D marine seismic reflection data.

Lyu et al. (2019) combined spectral decomposition with structure-oriented filtering to improve the signal-to-noise ratio and coherence, though it

**Table 4** Review of fault detection from seismic data using adaptive learning algorithms

Reference	Techniques used	Significance	Limitations
Zini et al. (2019)	SeisNet	Achieved high F1 score on bright spot recognition, quantifying bright spots, and predicting volume	Further research is needed for processing seismic data, waveform prediction, and performance on larger datasets
Zhou et al. (2021)	Transfer learning with convolutional neural networks	Quick training, produced satisfactory results despite the class imbalance	Inaccuracy in detecting fault discontinuities in 3D space
Cunha et al. (2020)	U-net based on DANN (Domain Adversarial Neural Network)	Improved fault detection accuracy, addressed challenges of real geological situations, noise disturbance, and seismic signal frequency	challenge in finishing fault detection on seismic data with various frequencies
Ao et al. (2021)	Transfer learning	Improved seismic dip estimation accuracy, applicability in real-world scenarios	Difficulty in assessing the reliability of network predictions
Dou et al. (2024)	Tiny Self-Attention and HRNet, contrastive learning	Enhanced representation learning, improved fault detection tasks, addressed memory overflow issues	Challenges in sparse distance matching in 3D high-resolution data
Zhou et al. (2021)	Progressive transfer learning	Enhanced fault detection using real seismic data, improved fault continuity	Difficulty in updating training dataset without introducing biases
Wei et al. (2022)	CNN and transfer learning	Robust fault feature representation learning, effective fault detection	Challenges in tuning focal loss parameters and ensuring effectiveness across different datasets
Li et al. (2024)	Fault-Attri-Attention	Improved fault detection with enhanced accuracy	Reduced efficiency and increased computational overhead due to managing multiple attributes
Mustafa et al. (2024)	3D CNN and Attention-guided training Framework	Enhanced fault prediction with better performance	Lack of deep understanding in modelling and incorporating human visual attention
Zeng et al. (2024)	3D-UNet	Enhanced feature extraction and fault detection, improved accuracy and continuity	Struggles in characterizing low-order faults and fault continuity
Zhang et al. (2022)	Deep Transfer Learning	Significantly accelerates hydraulic fracture imaging through deep transfer learning	Reliance on simplified models that introduce approximation errors
Titos et al. (2023)	Transfer Learning	Enhances real-time volcano tectonic earthquake monitoring through transfer learning	The quality and completeness of the master dataset introduce biases

tended to oversimplify complex fault networks. Yan et al. (2021) used transfer learning to fine-tune the pre-trained networks on real seismic data, enhancing fault classification accuracy but underscoring the need for improved models to achieve their full potential. Meanwhile, Lauden et al. (2021) integrated supervised deep learning with unsupervised multi-attribute classification to enhance fault interpretation. While this approach improved feature extraction, it struggled to maintain feature invariance in noisy environments.

Yuan et al. (2019) introduced an adaptive spectrum decomposition methodology combined with super-resolution deep learning to enhance frequency resolution in fault detection. Similarly, Otchere et al. (2022) applied pre-trained deep residual U-net CNNs for fault identification, achieving notable success in complex sub-salt formations. Zhang et al. (2024) proposed a 3D Transformer-based network-based self-supervised

learning methodology for feature extraction in fault recognition, which significantly enhanced accuracy with unlabelled data but still requires refinement to address the diverse nature of faults.

Mahadik et al. (2021) combined multispectral coherence with wavelet transforms to improve the detection of faults and stratigraphic structures, achieving promising results on real field seismic data. However, they noted the challenges of achieving full automation. Isaac et al. (2023) applied dip-steered filters to improve fault resolution but struggled to effectively differentiate between useful and noisy signals, highlighting the need for more advanced filtering techniques. Sheng et al. (2022) presented a high-quality earthquake catalog, emphasizing the role of hydraulic fracturing as a source of seismicity. However, their approach was limited by the absence of long-term observational data, pointing to the necessity of advanced modelling techniques.

To assess the risks of active faults associated with Enhanced Geothermal System activities, Feng et al. (2022) analyzed the stress fields in Tangshan under increased pore pressure. Although their findings contributed to seismic risk evaluation, their models struggled with pressure complexities, indicating the need for further refinement.

Table 5 presents the various advanced seismic data fault detection models, including Forward and Backward Diffusion, Structure-Oriented Filtering, Erosion Algorithm, Sobel and Laplacian of Gaussian, Gradient Structure Tensor-Based Coherence, Dip-Steered Diffusion Filter, Differential Structure Method, and Feature Enhancement Filtering.

## 2 Comparison of performance of various Machine Learning and Deep Learning techniques for fault detection from seismic data

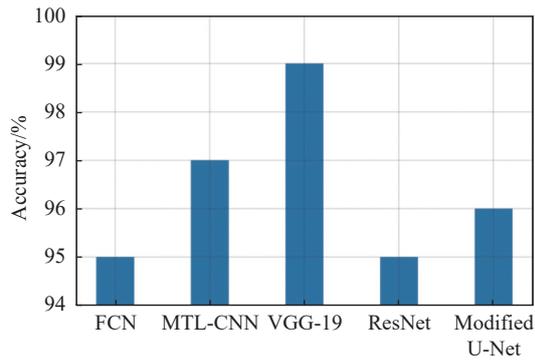
The comparative analysis of various algorithms discussed in this work for fault detection from seismic data is presented in this section.

Fig. 2 presents the comparative accuracy of existing fault detection techniques under both ML and DL methodologies. The graph highlighted that FCN (Noori et al. 2019) achieves an accuracy of 95%, MTL-CNN (Ren et al. 2023) achieves 97%, VGG 19 (Hu et al. 2020) achieves 99%, ResNet (Xu et al. 2021) reaches 95%, and Modified U-Net (Bi et al. 2021) achieves 96%. Among these techniques, VGG 19 exhibits the highest accuracy, indicating its superior performance and reliability in fault detection tasks. This suggests that VGG 19 excels in generalizing to unseen data, effectively distinguishing faults while minimizing errors, and ensuring consistent performance across diverse test datasets.

Fig.3 presents a comparative analysis of the loss metrics for existing fault detection techniques using ML and DL methods. The graph shows that FCN (Noori et al. 2019) converges to 0.01, MTL-

**Table 5** Review of enhanced fault detection models from seismic data

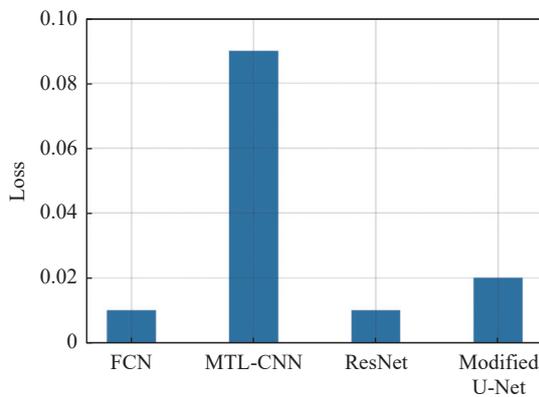
Reference	Techniques used	Significance	Limitations
Yan et al. (2019)	Forward and backward diffusion	Enhancing fault features while suppressing noise, improving fault-tracking accuracy	Struggles in differentiating actual faults and stratigraphic features in complex geological structures
Mousavi et al. (2022)	Erosion algorithm, Sobel and Laplacian of Gaussian	Potential alternative to conventional fault enhancement methods	Artificial enhancements or suppressions near boundaries affect overall image quality
Lyu et al. (2019)	Structure-oriented filtering	Improved fault identification through coherence enhancement	Introduction of spurious features or oversimplification of complex fault networks
Yan et al. (2021)	Transfer learning	Enhanced fault detection accuracy, particularly for complex fault types	Difficulty in accurately identifying complex fault types such as thrust and listric faults
Laudon et al. (2021)	CNN-SOM	Better outcomes compared to using single ML techniques	Lack of feature design invariant to variations such as noise, resolution, or acquisition parameters
Yuan et al. (2019)	Adaptive spectrum decomposition and super-resolution DL with CNN	Improved fault-detection system with adjustable scale highlighting and high-resolution	Bridging the gap between domains and fostering collaboration
Otchere et al. (2022)	Deep Residual U-net	Respectable fault prediction result, enhanced seismic imaging	Struggles to understand uncertainty inherent in predictions
Zhang et al. (2024)	FaultSeg Swin-UNet Transformer	Improved feature representations, increased recognition accuracy	Adaptability challenges with narrow, elongated, and unevenly distributed fault annotations
Mahadik et al. (2021)	Gradient structure tensor-based coherence	Clearer fault lines with less noise, future goal of creating automated defect detection system	Future integration of DL and ML is needed for complete automation
Isaac et al. (2023)	Dip-steered diffusion filter, DSMF and FEF	Revealing small-scale faults and stratigraphic heterogeneity	Need for improvement in noise suppression while preserving useful signal information
Sheng et al. (2022)	REST and hypoDD	Mechanisms of induced seismicity through fluid diffusion and fault reactivation	Limited by the lack of long-term observational data and potential variability
Feng et al. (2022)	Enhanced Geothermal System (EGS)	Offers a quantitative framework for assessing fault slip potential during geothermal operations	Limited by uncertainties in stress field parameters



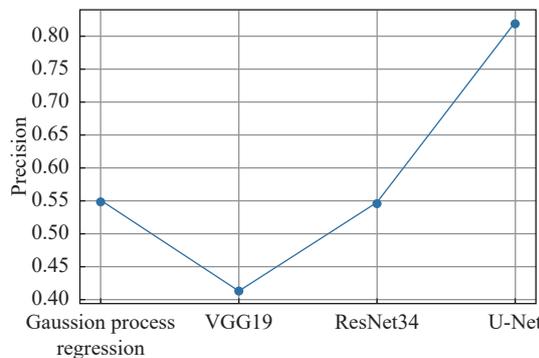
**Fig. 2** Comparative analysis of the accuracy of existing fault detection techniques

CNN (Ren et al. 2023) converges to 0.09, Modified U-Net (Bi et al. 2021) converges to 0.01, and CNN (Hu et al. 2020) converges to 0.02. This analysis reveals that FCN and Modified U-Net exhibit lower loss values, indicating their superior effectiveness in fault detection. However, despite these promising results, challenges remain, particularly in addressing complex geological features, which still pose difficulties in the application of these techniques.

Fig. 4 presents a comparative analysis of the



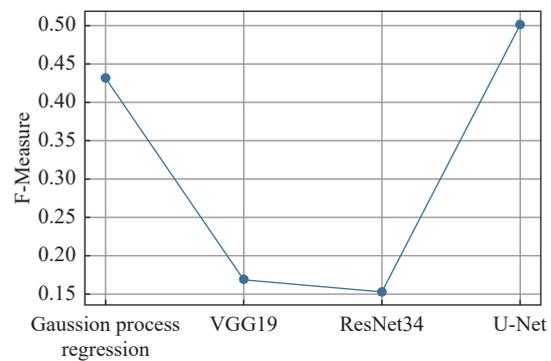
**Fig. 3** Comparative analysis of loss of existing fault detection techniques



**Fig. 4** Comparative analysis of precision of existing fault detection techniques

precision metrics for existing fault detection techniques using ML and DL methods. The graph shows that Gaussian process regression (Martín-Martín et al. 2023) achieves a precision of 0.55, VGG19 (Hu et al. 2020) achieves 0.41, ResNet (Xu et al. 2021) achieves 0.55 and U-Net (Liu et al. 2020) achieves 0.82. This analysis reveals that U-Net outperforms the other techniques in terms of precision, demonstrating its superior ability to accurately identify faults. Its higher precision indicates that U-Net is a highly reliable model for fault detection tasks, ensuring more accurate results in fault identification.

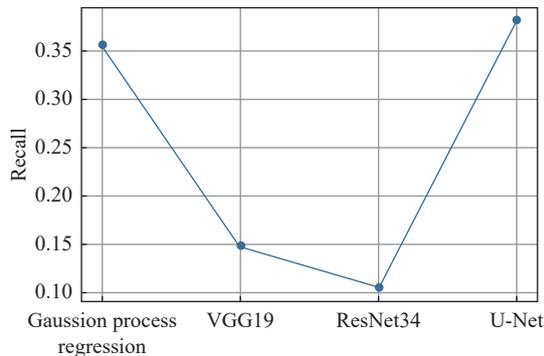
Fig. 5 presents a comparative analysis of the f-measure for existing fault detection techniques using ML and DL methods. The graph shows that f-measure for Gaussian process regression (Martín-Martín et al. 2023) is 0.43, VGG19 (Hu et al. 2020) is 0.17, ResNet (Li et al. 2019) is 0.15 and U-Net (Liu et al. 2020) is 0.50. This analysis highlights that U-Net is highly effective in fault detection, demonstrating the highest f-measure. A high f-measure indicates a strong balance between precision and recall, meaning U-Net not only identifies faults accurately but also minimizes false positives and false negatives. This makes U-Net a highly reliable model for fault detection, offering both sensitivity and specificity in complex tasks.



**Fig. 5** Comparative analysis of F-measure of existing fault detection techniques

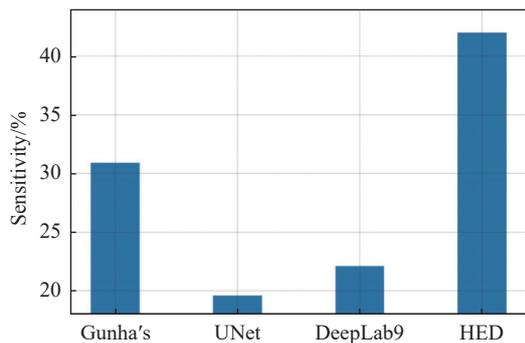
Fig. 6 presents the comparative analysis of recall metrics for existing fault detection techniques using ML and DL methods. The graph shows that the recall for Gaussian process regression (Martín-Martín et al. 2023) accomplishes 0.36, VGG19 (Hu et al. 2020) accomplishes 0.15, ResNet (Li et al. 2019) accomplishes 0.11 and U-Net (Liu et al. 2020) accomplishes 0.38. This analysis thus elucidates that U-Net is highly effective in fault detection, demonstrating the highest recall. A higher recall indicates that U-Net is more capable of identifying faults, minimizing the number of false

negatives. This makes U-Net particularly valuable in scenarios where it is crucial to detect as many faults as possible, ensuring a higher sensitivity to potential issues.



**Fig. 6** Comparative analysis of Recall of existing fault detection techniques

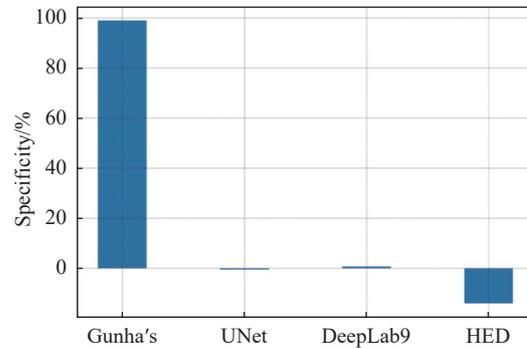
Fig. 7 presents the comparative analysis of sensitivity for existing fault detection techniques, such as Cunha's, UNet, DeepLab9 and HED (An et al. 2021), using ML and DL approaches. From the graph, it is evident that the sensitivity performance for Cunha's technique achieves 30.9%, U-Net achieves 19.6%, DeepLab9 achieves 22.1%, and HED achieves 42%. This analysis shows that HED is the most effective in fault detection, demonstrating the highest sensitivity. A higher sensitivity indicates that HED is more capable of correctly identifying faults, minimizing false negatives. This makes HED particularly valuable in fault detection tasks where it is crucial to detect as many true faults as possible.



**Fig. 7** Comparative analysis of sensitivity of existing fault detection techniques

Fig. 8 presents the comparative analysis of specificity for existing fault detection techniques, such as Cunha's, U-Net, DeepLab9, and HED (An et al. 2021) using ML and DL approaches. From the graph, it is evident that the specificity performance for Cunha's technique achieves 98.9%, U-Net achieves -0.5%, DeepLab9 achieves -0.6%, and HED achieves -14%. This analysis reveals

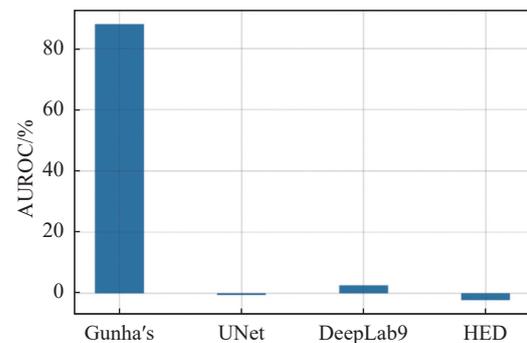
that Cunha's technique is the most effective in fault detection, demonstrating the highest specificity. A higher specificity indicates that Cunha's technique is more proficient at correctly identifying non-fault areas, minimizing false positives. This makes Cunha's technique particularly valuable in fault detection tasks where it is crucial to accurately classify non-fault regions.



**Fig. 8** Comparative analysis of specificity of existing fault detection techniques

Fig. 9 presents the comparative analysis of AUROC for existing fault detection techniques such as Cunha's, U-Net, DeepLab9, and HED (An et al. 2021) under ML and DL for AUROC metrics. From the graph, it is evident that the AUROC performance for Cunha's technique achieves 88%, U-Net achieves -0.5%, DeepLab9 achieves 2.6%, and HED achieves -2.3%. This analysis reveals that Cunha's technique is the most effective in fault detection, demonstrating the highest AUROC. A higher AUROC indicates that Cunha's technique is better at distinguishing between fault and non-fault regions, minimizing classification errors. This makes Cunha's technique particularly valuable in fault detection tasks where it is crucial to have a model with strong discriminatory power.

The overall comparison of existing techniques such as Gaussian process regression, VGG,



**Fig. 9** Comparative analysis of AUROC of existing fault detection techniques

ResNet, and U-Net revealed that, in terms of precision, U-Net performs better than other techniques. Similarly, for the F-measure, U-Net outperforms Gaussian process regression, VGG, and ResNet. The recall metric also demonstrates improved performance with U-Net compared to the other techniques. When comparing the training and validation accuracy of FCN, MTL-CNN, Modified U-Net, and CNN, VGG proves to be more effective in fault detection than the other techniques. Additionally, FCN and Modified U-Net show greater effectiveness in fault detection, with lower training and validation loss compared to the other techniques.

### 3 Conclusion and future scope

This work reviews the techniques used for fault detection from seismic data, discussing various approaches such as fault segmentation, fault detection using Machine Learning (ML), Deep Learning (DL), Adaptive Learning and Enhanced Learning techniques. The effectiveness and limitations of each technique are examined.

In fault segmentation, techniques such as Fault-Seg Net, CNN, FCN, and DNFS are compared. For fault detection in seismic data, ML algorithms like SVM, CNN, KNN, RF, FCN, and Gaussian process regression have been shown to achieve effective detection accuracy. However, these methods suffer from limitations, including ineffectiveness in dealing with non-stationary noise patterns, an inability to incorporate physical and geological constraints, and difficulty in capturing temporal fault patterns.

Similarly, when DL techniques such as GCN, DCNN, U-Net, and Encoder-Decoder deep neural networks are employed for fault detection, they yield significant results but face challenges like label discrepancies, computational optimization issues, model overfitting, and class imbalance.

Adaptive learning techniques, such as SeisNet, U-Net-based DANN, Self-attention, Fault-Attri-Attention, and 3D-UNet, also face challenges, including inaccuracy in detecting fault discontinuity, reliability concerns, dataset bias during updates, and difficulties in characterizing low-order faults and fault continuity.

Enhanced learning techniques, including Forward and backward diffusion, Structure-oriented filtering, Erosion algorithm, Sobel and Laplacian of Gaussian, Gradient structure tensor-based coherence, Dip-steered diffusion filter, DSMF, and FEF, present challenges such as diffi-

culty in distinguishing faults from other features in complex geological structures, uncertainty in predictions, lack of feature invariance, and noise suppression issues.

Despite the high potential of ML and DL in seismic fault detection, several critical challenges remain. These include high computational costs due to the model complexity, the integration of geological constraints, handling of non-stationary noise patterns, and label inconsistencies, which often lead to model overfitting. Addressing these challenges will require the design of application-specific architectures and optimization techniques that lessen the computational burden, incorporate domain knowledge, and effectively handle noise patterns, thereby enhancing the robustness and accuracy of fault detection systems in seismic data analysis.

Some of the critical areas that future research should focus on include the development of efficient model architectures and optimization methods to reduce computational overhead. Advanced algorithms are needed to incorporate geological constraints effectively. Semi-supervised learning techniques, along with methods for synthetic data generation, can help address problems related to label discrepancies and overfitting. Ensemble, and active learning approaches could also enhance the reliability and adaptability of models. Additionally, implementing advanced attention mechanisms within neural networks, integrated with deep geological context, holds great promise for significantly improving fault detection accuracy, especially in complex geologic settings.

### References

- Alfarhan M, Deriche M, Maalej A, et al. 2020. Multiple events detection in seismic structures using a novel U-Net variant. In 2020 IEEE International Conference on Image Processing (ICIP), 2900-2904, IEEE. DOI: [10.1109/ICIP40778.2020.9190682](https://doi.org/10.1109/ICIP40778.2020.9190682).
- Alfarhan M, Maalej A, Deriche M. 2020. Concurrent detection of salt domes and faults using resnet with u-net. In 2020 6th Conference on Data Science and Machine Learning Applications (CDMA), 118–122, IEEE. DOI: [10.1109/CDMA47397.2020.00026](https://doi.org/10.1109/CDMA47397.2020.00026).
- Alfarhan M, Deriche M, Maalej A. 2020. Robust concurrent detection of salt domes and faults in seismic surveys using an improved UNet architecture. *IEEE access*, 10: 39424–39435.

- DOI: [10.1109/ACCESS.2020.3043973](https://doi.org/10.1109/ACCESS.2020.3043973).
- Aloisio A, Battista LD, Alaggio R, et al. 2021. Assessment of structural interventions using Bayesian updating and subspace-based fault detection methods: The case study of S. Maria di Collemaggio basilica, L'Aquila, Italy. *Structure and Infrastructure Engineering*, 17(2): 141–155. DOI: [10.1080/15732479.2020.1731559](https://doi.org/10.1080/15732479.2020.1731559).
- An Y, Guo J, Ye Q, et al. 2021. Deep convolutional neural network for automatic fault recognition from 3D seismic datasets. *Computers & Geosciences*, 153: 104776. DOI: [10.1016/j.cageo.2021.104776](https://doi.org/10.1016/j.cageo.2021.104776).
- Ao Y, Lu W, Xu P, et al. 2021. Seismic dip estimation with a domain knowledge constrained-transfer learning approach. *IEEE Transactions on Geoscience and Remote Sensing*, 60: 1–16. DOI: [10.1109/TGRS.2021.3061438](https://doi.org/10.1109/TGRS.2021.3061438).
- Ashraf U, Zhang H, Anees A, et al. 2020. Application of unconventional seismic attributes and unsupervised machine learning for the identification of fault and fracture network. *Applied Sciences*, 10(11): 3864. DOI: [10.3390/app10113864](https://doi.org/10.3390/app10113864).
- Bi Z, Wu X, Geng Z, et al. 2021. Deep relative geologic time: A deep learning method for simultaneously interpreting 3 - D seismic horizons and faults. *Journal of Geophysical Research: Solid Earth*, 126(9): e2021JB021882. DOI: [10.1029/2021JB021882](https://doi.org/10.1029/2021JB021882).
- Cunha A, Pochet A, Lopes H, et al. 2020. Seismic fault detection in real data using transfer learning from a convolutional neural network pre-trained with synthetic seismic data. *Computers & Geosciences*, 135: 104344. DOI: [10.1016/j.cageo.2019.104344](https://doi.org/10.1016/j.cageo.2019.104344).
- Di H, Li C, Smith S, et al. 2021. Imposing interpretational constraints on a seismic interpretation convolutional neural network. *Geophysics*, 86(3): IM63–IM71. DOI: [10.1190/geo2020-0449.1](https://doi.org/10.1190/geo2020-0449.1).
- Dou Y, Li K, Zhu J, et al. 2021. Attention-based 3-D seismic fault segmentation training by a few 2-D slice labels. *IEEE Transactions on Geoscience and Remote Sensing*, 60: 1–15. DOI: [10.1109/TGRS.2021.3113676](https://doi.org/10.1109/TGRS.2021.3113676).
- Dou Y, Li K, Zhu J, et al. 2022. MD loss: Efficient training of 3-D seismic fault segmentation network under sparse labels by weakening anomaly annotation. *IEEE Transactions on Geoscience and Remote Sensing*, 1–13.
- Dou YM, Li KW, Dong MH, et al. 2024. Fault-SSL: Seismic fault detection via semisupervised learning. *Geophysics*, 89(3): M79–M91. DOI: [10.1190/geo2023-0550.1](https://doi.org/10.1190/geo2023-0550.1).
- Dou YM, Li KW. 2024. 3D seismic fault detection via contrastive-reconstruction representation learning. *Expert Systems with Applications*, 123617. DOI: [10.1016/j.eswa.2024.123617](https://doi.org/10.1016/j.eswa.2024.123617).
- Feng C, Gao G, Zhang S, et al. 2022. Fault slip potential induced by fluid injection in the Matouying enhanced geothermal system (EGS) field, Tangshan seismic region, North China. *Natural Hazards and Earth System Sciences*, 22(7): 2257–2287. DOI: [10.5194/nhess-22-2257-2022](https://doi.org/10.5194/nhess-22-2257-2022).
- Feng T, Zhang M, Xu L, et al. 2022. Machine learning - based earthquake catalog and tomography characterize the middle - northern section of the Xiaojiang fault zone. *Seismological Society of America*, 93(5): 2484–2497. DOI: [10.1785/0220220116](https://doi.org/10.1785/0220220116).
- Gong Y, Zhu C, Zhu G, et al. 2024. Seismic fault identification in coal mines based on the self-organizing map-gray wolf optimizer-support vector machine algorithm. *Interpretation*, 12(1): B1–B15. DOI: [10.1190/INT-2023-0025.1](https://doi.org/10.1190/INT-2023-0025.1).
- He T, Wu B, Zhu X. 2021. Seismic data consecutively missing trace interpolation based on multistage neural network training process. *IEEE Geoscience and Remote Sensing Letters*, 19: 1–5. DOI: [10.1109/LGRS.2021.3089585](https://doi.org/10.1109/LGRS.2021.3089585).
- Hosseini-Fard E, Roshandel-Kahoo A, Soleimani-Monfared M, et al. 2022. Automatic seismic image segmentation by introducing a novel strategy in histogram of oriented gradients. *Journal of Petroleum Science and Engineering*, 209: 109971. DOI: [10.1016/j.petrol.2021.109971](https://doi.org/10.1016/j.petrol.2021.109971).
- Hu G, Hu Z, Liu J, et al. 2020. Seismic fault interpretation using deep learning-based semantic segmentation method. *IEEE Geoscience and Remote Sensing Letters*, 19: 1–5. DOI: [10.1109/LGRS.2020.3041301](https://doi.org/10.1109/LGRS.2020.3041301).
- Isaac DB, Abu El Ata AS. 2023. Improvement of seismic data quality and recognition of fault

- discontinuities through seismic data conditioning applications: A case study of Issaran oil field, Gulf of Suez, Egypt. *Journal of Petroleum Exploration and Production Technology*, 13(2): 591–607. DOI: [10.1007/s13202-022-01574-2](https://doi.org/10.1007/s13202-022-01574-2).
- Jang J, So BD, Yuen DA. 2023. A machine learning algorithm with random forest for recognizing hidden control factors from seismic fault distribution. *Geosciences Journal*, 27(1): 113–126. DOI: [10.1007/s12303-022-0029-7](https://doi.org/10.1007/s12303-022-0029-7).
- Khayer K, Hosseini Fard E, Roshandel Kahoo A, et al. 2023. Integration of feature extraction, attribute combination and image segmentation for object delineation on seismic images. *Acta Geophysica*, 71(1): 275–292. DOI: [10.1007/s11600-022-00921-5](https://doi.org/10.1007/s11600-022-00921-5).
- Laudon C, Qi J, Rondon A, et al. 2021. An enhanced fault detection workflow combining machine learning and seismic attributes yields an improved fault model for Caspian Sea asset. *First break*, 39(10): 53–60. DOI: [10.3997/1365-2397.fb2021075](https://doi.org/10.3997/1365-2397.fb2021075).
- Lefevre M, Souloumiac P, Cubas N, et al. 2020. Experimental evidence for crustal control over seismic fault segmentation. *Geology*, 48(8): 844–848. DOI: [10.1130/G47115.1](https://doi.org/10.1130/G47115.1).
- Li JT, Wu XM, Hu ZX. 2021. Deep learning for simultaneous seismic image super-resolution and denoising. *IEEE Transactions on Geoscience and Remote Sensing*, 60: 1–11. DOI: [10.1109/TGRS.2021.3057857](https://doi.org/10.1109/TGRS.2021.3057857).
- Li S, Yang C, Sun H, et al. 2019. Seismic fault detection using an encoder–decoder convolutional neural network with a small training set. *Journal of Geophysics and Engineering*, 16(1): 175–189. DOI: [10.1093/jge/gxy015](https://doi.org/10.1093/jge/gxy015).
- Li W, Wang J. 2021. Residual learning of cycle-GAN for seismic data denoising. *IEEE access*, 9: 11585–11597. DOI: [10.1109/ACCESS.2021.3049479](https://doi.org/10.1109/ACCESS.2021.3049479).
- Li X, Li K, Xu Z, et al. 2023. Fault-Seg-Net: A method for seismic fault segmentation based on multi-scale feature fusion with imbalanced classification. *Computers and Geotechnics*, 158: 105412. DOI: [10.1016/j.compgeo.2023.105412](https://doi.org/10.1016/j.compgeo.2023.105412).
- Li X, Li K, Xu Z, et al. 2024. Fault-Seg-LNet: A method for seismic fault identification based on lightweight and dynamic scalable network. *Engineering Applications of Artificial Intelligence*, 127: 107316. DOI: [10.1016/j.engappai.2023.107316](https://doi.org/10.1016/j.engappai.2023.107316).
- Li X, Li, K. 2024. Fault-attrib-attention: A method for fault identification based on seismic attributes attention. *Neural Computing and Applications*, 36(7): 3645–3661. DOI: [10.1007/s00521-023-09265-7](https://doi.org/10.1007/s00521-023-09265-7).
- Lima G, Zeiser FA, Da Silveira A, et al. 2024. An encoder–decoder deep neural network for binary segmentation of seismic facies. *Computers & Geosciences*, 183: 105507. DOI: [10.1016/j.cageo.2023.105507](https://doi.org/10.1016/j.cageo.2023.105507).
- Lin L, Zhong Z, Cai Z, et al. 2022. Automatic geologic fault identification from seismic data using 2.5 D channel attention U-net. *Geophysics*, 87(4): IM111–IM124. DOI: [10.1190/geo2021-0805.1](https://doi.org/10.1190/geo2021-0805.1).
- Liu ZN, Zhou C, Hu GM, et al. 2020, May. Interpretability-guided convolutional neural networks for seismic fault segmentation. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 4312–4316). IEEE. DOI: [10.1109/ICASSP40776.2020.9053472](https://doi.org/10.1109/ICASSP40776.2020.9053472).
- Lyu B, Qi J, Machado G, et al. 2019. Seismic fault enhancement using spectral decomposition assisted attributes. In SEG Technical Program Expanded Abstracts. Society of Exploration Geophysicists: 1938–1942. DOI: [10.1190/segam2019-3215703.1](https://doi.org/10.1190/segam2019-3215703.1).
- Ma X, Yao G, Zhang F, et al. 2023. 3D Seismic Fault Detection Using Recurrent Convolutional Neural Networks with Compound Loss. *IEEE Transactions on Geoscience and Remote Sensing*, 61: 1–15. DOI: [10.1109/TGRS.2023.3275951](https://doi.org/10.1109/TGRS.2023.3275951).
- Mahadik R, Singh G, Routray A. 2021. Multispectral coherence analysis for better fault visualization in seismic data. *IEEE Geoscience and Remote Sensing Letters*, 19: 1–5. DOI: [10.1109/LGRS.2021.3076213](https://doi.org/10.1109/LGRS.2021.3076213).
- Michie EA, Mulrooney MJ, Braathen A. 2021. Fault interpretation uncertainties using seismic data, and the effects on fault seal analysis: A case study from the Horda Platform, with implications for CO2 storage. *Solid Earth Discussions*, 12(6): 1259–1286. DOI: [10.5194/se-12-1259-2021](https://doi.org/10.5194/se-12-1259-2021).
- Mizutani A, Yomogida K, Tanioka Y. 2020. Early

- tsunami detection with near-fault ocean-bottom pressure gauge records based on the comparison with seismic data. *Journal of Geophysical Research: Oceans*, 125(9): e2020JC016275. DOI: [10.1029/2020JC016275](https://doi.org/10.1029/2020JC016275).
- Martín-Martín M, Bullejos M, Cabezas D, et al. 2023. Using Python libraries and k-Nearest neighbors algorithms to delineate syn-sedimentary faults in sedimentary porous media. *Marine and Petroleum Geology*, 153: 106283. DOI: [10.1016/j.marpetgeo.2023.106283](https://doi.org/10.1016/j.marpetgeo.2023.106283).
- Mousavi J, Radad M, Soleimani Monfared M, et al. 2022. Fault enhancement in seismic images by introducing a novel strategy integrating attributes and image analysis techniques. *Pure and Applied Geophysics*, 179(5): 1645–1660. DOI: [10.1007/s00024-022-03014-y](https://doi.org/10.1007/s00024-022-03014-y).
- Mustafa A, Rastegar R, Brown T, et al. 2024. Visual attention guided learning with incomplete labels for Seismic Fault Interpretation. *IEEE Transactions on Geoscience and Remote Sensing*, 62: 1–12. DOI: [10.1109/TGRS.2024.3370037](https://doi.org/10.1109/TGRS.2024.3370037).
- Noori M, Hassani H, Javaherian A, et al. 2019. Automatic fault detection in seismic data using Gaussian process regression. *Journal of Applied Geophysics*, 163: 117–131. DOI: [10.1016/j.jappgeo.2019.02.018](https://doi.org/10.1016/j.jappgeo.2019.02.018).
- Otchere DA, Tackie-Otoo BN, Mohammad MAA, et al. 2022. Improving seismic fault map through data conditioning using a pre-trained deep convolutional neural network: A case study on Groningen field. *Journal of Petroleum Science and Engineering*, 213: 110411. DOI: [10.1016/j.petrol.2022.110411](https://doi.org/10.1016/j.petrol.2022.110411).
- Palo P, Routray A, Mahadik R, et al. 2023. Fault detection in seismic data using graph convolutional network. *The Journal of Supercomputing*, 79(11): 12737–12765. DOI: [10.1007/s11227-023-05173-8](https://doi.org/10.1007/s11227-023-05173-8).
- Ren K, Zou G, Zhang S, et al. 2023. Fault identification and reliability evaluation using an SVM model based on 3-D seismic data volume. *Geophysical Journal International*, 234(1): 755–768. DOI: [10.1093/gji/ggad095](https://doi.org/10.1093/gji/ggad095).
- Share PE, Allam AA, Ben-Zion Y, et al. 2019. Structural properties of the San Jacinto fault zone at Blackburn Saddle from seismic data of a dense linear array. *Pure and Applied Geophysics*, 176: 1169–1191. DOI: [10.1007/s00024-018-1988-5](https://doi.org/10.1007/s00024-018-1988-5).
- Sheng M, Chu R, Peng Z, et al. 2022. Earthquakes triggered by fluid diffusion and boosted by fault reactivation in Weiyuan, China due to hydraulic fracturing. *Journal of Geophysical Research: Solid Earth*, 127(5): e2021JB022963. DOI: [10.1029/2021JB022963](https://doi.org/10.1029/2021JB022963).
- Titos M, Gutiérrez L, Benítez C, et al. 2023. Multi-station volcano tectonic earthquake monitoring based on transfer learning. *Frontiers in Earth Science*, 11: 1204832. DOI: [10.3389/feart.2023.1204832](https://doi.org/10.3389/feart.2023.1204832).
- Ul Islam MS. 2020. Using deep learning-based methods to classify salt bodies in seismic images. *Journal of Applied Geophysics*, 178: 104054. DOI: [10.1016/j.jappgeo.2020.104054](https://doi.org/10.1016/j.jappgeo.2020.104054).
- Visini F, Valentini A, Chartier T, et al. 2020. Computational tools for relaxing the fault segmentation in probabilistic seismic hazard modelling in complex fault systems. *Pure and Applied Geophysics*, 177: 1855–1877. DOI: [10.1007/s00024-019-02114-6](https://doi.org/10.1007/s00024-019-02114-6).
- Vu MT, Jardani A. 2022. Mapping discrete fracture networks using inversion of hydraulic tomography data with convolutional neural network: SegNet-Fracture. *Journal of Hydrology*, 609: 127752. DOI: [10.1016/j.jhydrol.2022.127752](https://doi.org/10.1016/j.jhydrol.2022.127752).
- Vu MT, Jardani, A. 2022. Multi-task neural network in hydrological tomography to map the transmissivity and storativity simultaneously: HT-XNET. *Journal of Hydrology*, 612: 128167. DOI: [10.1016/j.jhydrol.2022.128167](https://doi.org/10.1016/j.jhydrol.2022.128167).
- Waheed UB, Alkhalifah T, Haghghat E, et al. 2021. PINNtomo: Seismic tomography using physics-informed neural networks. arXiv preprint arXiv: 2104.01588. DOI: [10.48550/arXiv.2104.01588](https://doi.org/10.48550/arXiv.2104.01588).
- Wang QZ, Zhu ZY, Ding JC, et al. 2023. Research and application of intelligent fault detection method based on multi-scale fusion and Enhancement. In International Field Exploration and Development Conference, Singapore: Springer Nature Singapore, 543–553. DOI: [10.1007/978-981-97-0483-5\\_53](https://doi.org/10.1007/978-981-97-0483-5_53).
- Wang Z, Li B, Liu N, et al. 2020. Distilling knowl-

- edge from an ensemble of convolutional neural networks for seismic fault detection. *IEEE Geoscience and Remote Sensing Letters*, 19: 1–5. DOI: [10.1109/LGRS.2020.3034960](https://doi.org/10.1109/LGRS.2020.3034960).
- Wei XL, Zhang CX, Kim SW, et al. 2022. Seismic fault detection using convolutional neural networks with focal loss. *Computers & Geosciences*, 158: 104968. DOI: [10.1016/j.cageo.2021.104968](https://doi.org/10.1016/j.cageo.2021.104968).
- Wu J, Liu B, Zhang H, et al. 2021. Fault detection based on fully convolutional networks (FCN). *Journal of Marine Science and Engineering*, 9(3): 259. DOI: [10.3390/jmse9030259](https://doi.org/10.3390/jmse9030259).
- Wu J, Shi Y, Wang W. 2022. Fault imaging of seismic data based on a modified u-net with dilated convolution. *Applied Sciences*, 12(5): 2451. DOI: [10.3390/app12052451](https://doi.org/10.3390/app12052451).
- Wu X, Liang L, Shi Y, et al. 2019. Multitask learning for local seismic image processing: fault detection, structure-oriented smoothing with edge-preserving, and seismic normal estimation by using a single convolutional neural network. *Geophysical Journal International*, 219(3): 2097–2109. DOI: [10.1093/gji/ggz418](https://doi.org/10.1093/gji/ggz418).
- Wu X, Liang L, Shi Y, et al. 2019. FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation. *Geophysics*, 84(3): IM35–IM45. DOI: [10.1190/geo2018-0646.1](https://doi.org/10.1190/geo2018-0646.1).
- Xu F, Li Z, Wen B, et al. 2021. The use of 3D convolutional autoencoder in fault and fracture network characterization. *Geofluids*, 1–11. DOI: [10.1155/2021/6650823](https://doi.org/10.1155/2021/6650823).
- Yan Z, Liu S, Gu H. 2019. Fault image enhancement using a forward and backward diffusion method. *Computers & Geosciences*, 131: 1–14. DOI: [10.1016/j.cageo.2019.06.004](https://doi.org/10.1016/j.cageo.2019.06.004).
- Yan Z, Zhang Z, Liu S. 2021. Improving performance of seismic fault detection by fine-tuning the convolutional neural network pre-trained with synthetic samples. *Energies*, 14(12): 3650. DOI: [10.3390/en14123650](https://doi.org/10.3390/en14123650).
- Yuan Z, Huang H, Jiang Y, et al. 2019. An enhanced fault-detection method based on adaptive spectral decomposition and super-resolution deep learning. *Interpretation*, 7(3): T713–T725. DOI: [10.1190/INT-2018-0180.1](https://doi.org/10.1190/INT-2018-0180.1).
- Zeng A, Yan L, Huang Y, et al. 2021. Intelligent detection of small faults using a support vector machine. *Energies*, 14(19): 6242. DOI: [10.3390/en14196242](https://doi.org/10.3390/en14196242).
- Zeng L, Niu Y, Ren W, et al. 2024. A method for intelligent identification of faults in seismic using an attention-based ES-UNet network with model re-training learning. *Journal of Applied Geophysics*, 105344. DOI: [10.1016/j.jappgeo.2024.105344](https://doi.org/10.1016/j.jappgeo.2024.105344).
- Zhang R, Sun Q, Mao Y, et al. 2022. Accelerating hydraulic fracture imaging by deep transfer learning. *IEEE Transactions on Antennas and Propagation*, 70(7): 6117–6121. DOI: [10.1109/TAP.2022.3161325](https://doi.org/10.1109/TAP.2022.3161325).
- Zhang Z, Chen R, Ma J. 2024. Improving seismic fault recognition with Self-Supervised Pre-Training: A Study of 3D transformer-based with multi-scale decoding and fusion. *Remote Sensing*, 16(5): 922. DOI: [10.3390/rs16050922](https://doi.org/10.3390/rs16050922).
- Zhou R, Yao X, Hu, G, et al. 2021. Learning from unlabelled real seismic data: Fault detection based on transfer learning. *Geophysical Prospecting*, 69(6): 1218–1234. DOI: [10.1111/1365-2478.13097](https://doi.org/10.1111/1365-2478.13097).
- Zhou R, Yao X, Wang Y, et al. 2021. Seismic fault detection with progressive transfer learning. *Acta Geophysica*, 69: 2187–2203. DOI: [10.1007/s11600-021-00668-5](https://doi.org/10.1007/s11600-021-00668-5).
- Zini JE, Rizk Y, Awad M. 2019. A deep transfer learning framework for seismic data analysis: A case study on bright spot detection. *IEEE Transactions on Geoscience and Remote Sensing*, 58(5): 3202–3212. DOI: [10.1109/TGRS.2019.2950888](https://doi.org/10.1109/TGRS.2019.2950888).