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Original Article

Seismic Fault Detection Using Convolutional and Transformer-Based Models

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Abstract:

Seismic fault detection is a critical component of subsurface characterization, reservoir evaluation, and geohazard analysis. Traditional approaches including manual interpretation, edge detection filters, and seismic attributes have contributed significantly to structural mapping but remain limited by subjectivity, sensitivity to noise, and challenges in handling complex 3D seismic volumes. Recent advances in deep learning have introduced powerful alternatives, particularly convolutional neural networks (CNNs) and transformer-based architectures, which can learn hierarchical and long-range structural patterns directly from seismic data. This review provides a comprehensive synthesis of studies employing CNNs, multi-scale networks, U-Net variants, attention modules, and early transformer models for automated fault detection. We examine their principles, architectures, datasets, evaluation metrics, strengths, and limitations in comparison to conventional methods. Furthermore, we analyze the role of hybrid CNN–Transformer frameworks and discuss challenges such as limited labeled data, computational constraints, and generalization across geological settings. Finally, we outline future research directions, including semi-supervised learning, domain-informed modeling, and scalable architectures suited for high-resolution 3D seismic interpretation.

Keywords:

Seismic Fault Detection, Convolutional Neural Networks (Cnns), Transformer Models, Deep Learning, 3D Seismic Interpretation, Hybrid Architectures.

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1. Introduction

Seismic fault identification is important in the exploration of hydrocarbons as well as the evaluation of the geohazard[1]. Faults in the seismic volumes can be correctly identified to enable the geoscientists to map the underground geology, assess reservoir compartmentalization and forecast areas of potential instability[2]. Faults may play an important role in influencing fluid flow, trapping and drilling safety, and their accurate identification is an important aspect of the subsurface interpretation [3]. Moreover, growing complexity of the underground information in recent 3D seismic surveys has led to the urgency of more automated and dependable techniques of fault detection. Although the traditional approaches are fundamental, they have a major challenge in managing these large and complex datasets effectively.

In the past, fault identification was dependent on a considerable amount of manual seismic section interpretation, and necessitated levels of expertise in the form of geoscientists with a visual sense of discontinuities and structural trends[4]. Although working well with small-scale studies, manual approaches are time consuming, subjective, and can be highly inconsistent, particularly when used with large 3D datasets. As a guide to interpretation, the seismic qualities of coherence, curvature and semblance have been extensively used to point out possible fault zones. The Edge detection methods such as Sobel, Canny and Hough transforms have also been used to improve discontinuities in seismic images[5]. Even with these developments, traditional attribute and edge methods tend to be sensitive to noisy data, subtle fault patterns, and complicated geological environments, and superior and automated strategies are needed.

The introduction of deep learning has given it promising options regarding seismic fault detection. Specifically, convolutional neural networks (CNNs) have proven themselves as efficient in the learning of spatial details of image-like seismic data so that the automatic detection and segmentation of faults can be achieved with minimal human involvement[6]. The CNNs are capable of identifying the hierarchical features at various levels, thus, identifying both prominent and subtle faults. Recently, transformer-based architectures have also demonstrated the ability to learn long-range dependencies in seismic volumes using self-attention mechanisms, but have not been adopted in geoscience[7]. These deep learning methods are more efficient, accurate, and generalized than the traditional methods, which has triggered a transition towards automated interpretation of fault.

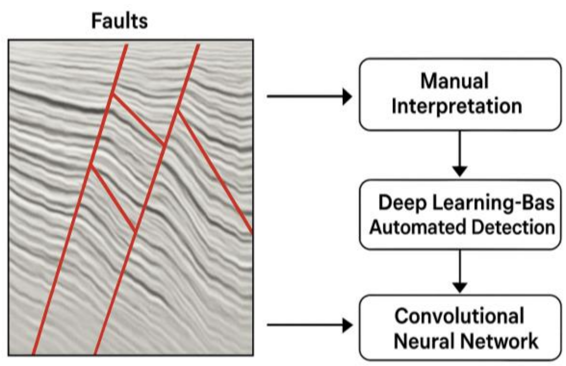

Figure 1. Seismic section illustrating faults alongside a comparative workflow

The current review is centered on the studies which involve CNNs and initial transformer-based models to detect seismic faults. Using a systematic analysis of existing techniques, architectures, datasets, and performance, this article would be able to present a general overview of the state-of-the-art, outline the current challenges in the field, and point to the future directions of new research in automated fault detection.

The key aims of this review are:

- To offer a systematic summary of CNN and transformer-based models that have been used on seismic faults.
- To condense data sets, architectures and performance indicators employed in these papers.
- To critically compare traditional methods with deep learning approaches, highlighting strengths and limitations.
- To determine the obstacles and possible future research on automated seismic fault interpretation.

Through the solutions to these objectives, the review will provide a clear picture of the state-of-the-art technologies to geoscientists and researchers as a basis of further advance in the automated fault detection.

2. Literature Review

The seismic faults are cracks or discontinuities in the underground surface of the earth where the layers of rocks move relative to each other as a result of the tectonic pressures [8]. They play a critical role in knowing geological structures, fluid migration pathways and geohazards and have a direct effect on reservoir compartmentalization and drilling safety. Proper formation faults in seismic volumes are required in hydrocarbon exploration, subsurface modeling and risk assessment.

The faults are broadly categorized depending on the relative motion of rock blocks. Normal faults arise in the case of an extensional regime, during which the hanging wall slides down relative to the footwall. Under compressional conditions, faults are formed in the reverse orientation, and the hanging wall moves upwards [9]. Strike-slip faults are the horizontal movements over a vertical fault plane. These types of faults can be seen in complex geological environments and combinations of these types can be difficult to interpret. Detection of the faults in the seismic data is based on the identification of both the geometric discontinuities and the attribute anomalies and the minor faults are sometimes hard to visually see [10].

Seismic properties have been extensively applied to increase the viewability of faults. The Coherence attributes test the similarity, similar to the average similarity, of the seismic traces in a local window, which is effectively used to identify discontinuities related to the faults [11]. Attributes of curvature, such as most-positive curvature, most-negative curvature and the dip curvature, describe the bending and flexure of horizons, which tend to depict folds and fault zones. Amplitude anomalies in some cases, these amplitude anomalies can be used to show that there is accumulation of fluids along a fault plane. These tools notwithstanding, it is difficult to detect faults in 3D seismic volumes, particularly in situations where the data are noisy, or the faults are fine. Automated methods are becoming very necessary to enhance efficiency and uniformity in seismic interpretation [12].

Before the deep learning methods, fault detection was dependent on manual interpretation and computation methods like edge detection and seismic attributes [13]. Manual interpretation, which is carried out by senior geoscientists, is precise but time consuming, and subjective especially when dealing with vast datasets of 3D seismics.

Methods of edge detection have a wide use in pointing out discontinuities. The Sobel operator involves taking a gradient of seismic amplitudes and puts more emphasis on edges whereas the Canny operator applies multi-stage filtering to capture sharp edges and minimize noise[14]. The Hough transform is suitable in the identification of linear features, especially in 2D sections or in edge-enhanced images. The techniques are effective with major faults but are unable to identify minor faults or overlapping faults.

The attribute-based technologies are used to improve the fault detection based on the local seismic properties. The similarity of traces measures discontinuities in coherence attributes [15]. Semblance points out structural offsets and curvature attributes detect bending and folding patterns which are often faults. Although these techniques enhance the visibility of faults, their success largely depends on the quality of the data, horizon picking, and choice of parameters:Table 1 provides an overview of the traditional methods of fault detection, their input and benefits as well as their limitations:

Table 1. Summary of conventional fault detection techniques

Method	Input	Advantages	Limitations
Manual Interpretation	Seismic sections	High accuracy, expert knowledge	Time-consuming, subjective
Sobel Edge Detection	Seismic amplitude	Highlights edges quickly	Sensitive to noise, misses subtle faults
Canny Edge Detection	Seismic amplitude	Reduces noise, better edge localization	Parameter-sensitive, may detect false edges
Hough Transform	Edge-enhanced images	Detects linear faults	Limited to simple fault geometries
Coherence Attribute	3D seismic volume	Highlights discontinuities	May fail with subtle faults, sensitive to noise
Curvature Attribute	3D seismic volume	Captures bending/flexure	Requires good horizon picking, parameter tuning
Semblance Attribute	3D seismic volume	Useful in velocity/structural analysis	Limited to specific applications

These very common methods have limitations because they are low in automation, sensitive to noise, and unavailable in generalization to different geological settings. These shortcomings formed the basis of deep learning methods that are able to acquire hierarchical features and provide automated fault detection.

Fig. 2 gives a small schematic comparing the edge detection and the attribute-based detection in a seismic section to explain the difference between the two approaches. The diagram underscores the fact that edge-based approaches accentuate sharpness of discontinuities as compared to attribute-based approaches that give a more continuous fault signal across larger volumes.

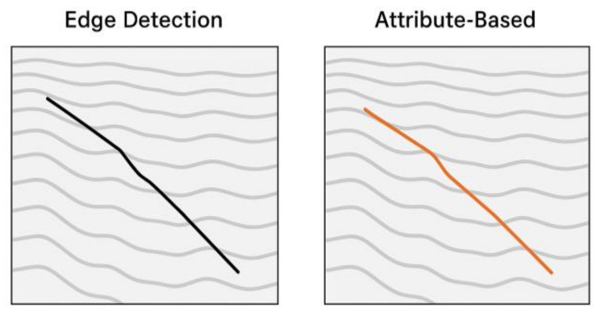

Figure 2. Comparison of edge detection and attribute-based seismic fault detection methods.

The seismic properties plus edge-detecting is still popular as an initial step in more sophisticated automated methods to facilitate a transition to convolutional neural networks and transformer-based models that could further enhance their accuracy and generalization.

3. Deep Learning Approaches for Fault Detection

The introduction of seismic acquisition technology and the increase in the amount of exploration data has rendered manual and attribute-based fault interpretation techniques to be inadequate [16]. Detection of faults is labor-intensive as well as biased on interpretation by the interpreter when carried out by traditional methods like coherence analysis, curvature attributes, and edge-detection filters. With the targets of exploration becoming more of a structural complex and the increased use of high-resolution 3D seismic surveys, the limitations of classical techniques especially in terms of automation, scale and geological consistency become more evident.

It is against this background that deep learning (DL) methods have become innovative methods of seismic interpretation. Early 2015 through 2020 Early experiments have shown that using DL models, specifically convolutional neural networks (CNNs), complex subsurface structures could be automatically determined using seismic data as input (either raw or minimally processed). By 2019, 3D CNNs and multi-scale architecture had demonstrated a good performance in fault segmentation jobs and they massively outperformed the traditional methods.

The last experiments with transformer-based models, first created to use natural language processing, were also observed in the late 2010s. Despite the fact that their use in seismic data was still limited, the use of transformers helped to put forward an entirely new mechanism of self-attention, which allowed the modeling of spatial dependence on a large distance in seismic volumes[17]. These processes provided the basis of hybrid and attention-enhanced interpretations in later years.

This section will extensively review the advances of deep learning in the field of seismic fault detection especially on the two basic architectures CNNs and transformers. It is sought to contrast their values, strengths, weaknesses and performance patterns in seismic fault segmentation work.

3.1. Convolutional Neural Networks (CNNs)

3.1.1. Principles of CNN Operation

Convolutional neural networks (CNNs) are grid-based structured data processing networks and hence suited to seismic sections and volumes [18]. They are comprised of the following:

- Convolution layers: These layers use small learned filters to identify meaningful local features (i.e. discontinuities or amplitude contrasts).
- Pooling layer: The downsampling of the spatial dimensions by pooling layers is done to reduce the computations and promote noise sensitivity and translation invariance.
- Activation functions: The activation functions are generally ReLU that provide non-linearity in the learning of intricate patterns.
- Feature hierarchies: The hierarchy of features in which subsequent layers of features of increasing abstraction are represented by edges and textures on to large structural dislocations such as faults.

This multi-level feature extraction finds application especially in seismic interpretation, where faults can be in the form of slight movements, discontinuities in reflectors or variations of amplitude due to lithology and to acquisition conditions.

3.1.2. Early Applications of CNNs to Seismic Fault Detection

Research was able to prove that CNNs worked really well in detecting errors in 2D and 3D seismic datasets. Some researchers used a full 3D CNN in fault segmentation. Their model handled seismic cubes and made predictions at the voxel level, which was estimated to be better than traditional coherence and curvature features [19]. The paper pointed out that 3D convolutions enabled the network to comprehend the continuity of geologic structures in adjacent slices to enhance fault connectivity forecasting.

Wang also came up with a powerful study when they created a multi-scale CNN aimed at capturing small and thin faults as well as large zones of displacement. [20] Multi-scale detectors either include convolutional filters of different sizes or feature pyramids to process seismic features with different resolutions. These designs are especially efficient in geologically complicated regions where the faults are thick and discontinuous at different locations.

Some researchers generalized CNN applications to 2D seismic slices through an encoder-decoder structure that resembled U-Net structures [21]. The encoder is trained to learn compressed codes of the seismic characteristics and the decoder is trained to decode full-scale fault probability maps. This method showed high generalization to invisible data, which showed that CNNs could extract useful structural features even when used on small numbers of training data.

3.1.3. CNN Architectural Variants for Fault Detection

A number of CNN architectural plans were experimented in seismic interpretation studies:

- Shallow vs. Deep CNNs:The networks with few layers (shallow networks) are cheap to compute and less likely to overfit on small data sets, but can also have difficulties with subtle patterns of faults [22]. Deep networks (many stacked convolution layers) are able to capture complex patterns but require additional training data as well as gpu resources.
- Encoder / U-Net Architectures.: These architectures were the most used in segmentation activities. Their skip-connections are the fused deep semantic and shallow spatial detail, which is useful in identifying small faults that otherwise would be lost in downsampling.
- 3D CNNs: The use of 3D convolutions is very effective in seismic interpretation since it provides volumetric context along both inline and crossline directions and time/depth. Early 3D CNNs (20182020) were constrained by computing power but had a higher accuracy of continuous fault monitoring.
- Multi-Scale CNNs: Multi-scale CNNs combine several receptive fields in order to deal with geological scenarios when faults are thick, dip, and intense differently. These architectures improved the performance of structurally intricate basins, which have intersecting or branching faults.

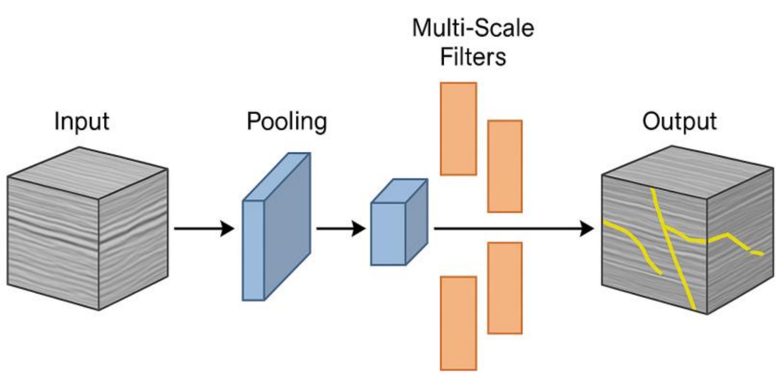

Figure 3. CNN architecture schematic for seismic fault detection.

3.1.4. Performance Trends and Limitations of CNNs

In quantitative tests, CNN models have always been better than classical fault attributes, in both precision and recall . Nevertheless, they were still controlled by:

- Labeled data availability
- Complexity and degree of networks.
- Hyperparameter tuning
- Augmentation and other training strategies.

To solve the problem of data paucity, the researchers employed random crop, flipping, amplitude scaling, and rotation. However, CNNs continued to struggle with:

- Extensive international environment (distant faults)
- Noisy seismic inputs
- Faults that are weak or discontinuous reflectively.

These issues inspired the search for solutions based on transformers that could be used to capture long-range relationships.

3.2. Transformer-Based Approaches

3.2.1. Principles of Transformers and Self-Attention

Transformers were invented to deal with sequential text data, however their self-attention algorithm can be extended to any structured input, such as seismic images [23]. Transformers, in contrast to CNNs, use self-attention to compute the relationship between positions in an input (e.g. pixel or voxel) on a global basis, each position then examining its significance to every other position.

This can be translated to the ability to in seismic data:

- Represent extensive geologic patterns.
- Model reflector continuity
- Also know how to play faults and horizons on each other
- Enhance the ability to identify small or low contrast discontinuities.

This processing across the globe is a major benefit of fault detection, in which faults can be spread across tens or hundreds of traces.

3.2.2. Early Adoption in Geoscience

The use of transformers in seismic interpretation was still in use but increasing. Prior research investigated attention-based feature extraction when the goal was structural interpretation as in:

- Horizon tracking
- Seismic segmentation
- Detection estimation probability of faults.

The augmentation of attention modules within regular CNNs enhanced the fault detection accuracy, especially of long and continuous faults. Their model, though not being a complete transformer, added attention maps that assisted in re-weighting the relevant regions of the seismic volume.

Its suggested a hybrid CNN + attention mechanism of 3D seismic fault localization. The attentiveness blocks served the purpose of transformer-like modules, through which the network was able to record the global structural backgrounds [24].

These initial experiments indicated that even partial attention adoption enhanced fault segmentation and there is high potential of a full transformer model in the future when the computational resources and seismic datasets had been available more broadly.

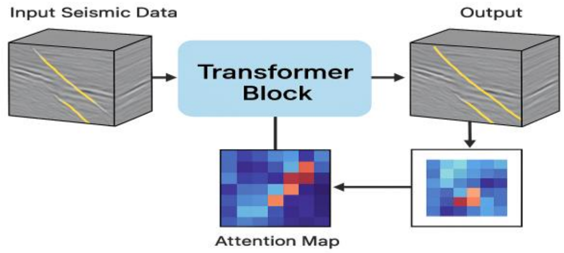

Figure 4. Transformer block / attention map applied to seismic data.

3.3. Advantages and Limitations of Transformers

3.3.1. Advantages

- Superior modeling of long-range dependencies
- Higher sensitivity to subtle faults
- Improved structural continuity mappingff
- Ability to complement CNN pipelines

3.3.2. Limitations

- High computational cost
- Need for large labeled datasets
- Limited availability of seismic transformer applications
- Difficulty training full 3D transformer networks with limited GPU memory

Despite these challenges, transformers showed early promise and foreshadowed the hybrid architectures that would emerge.

The following table summarizes key studies involving CNNs, attention mechanisms, and early transformer variants .

Table 2. Summary of CNN and Transformer Studies

Dataset	Architecture	Performance
3D seismic volume	3D CNN	High precision and recall
Multi-scale seismic	Multi-scale CNN	Detected small & large faults effectively
2D slices	Encoder-decoder CNN	Strong dataset generalization
Horizons	Transformer (self-attention)	Improved subtle fault detection
3D seismic	Hybrid CNN + attention	Enhanced localization with context-aware features

4. Comparative Analysis and Discussion

The swift adoption of deep learning technologies in seismic fault detection has introduced numerous architectures and methodologies with the most remarkable ones being convolutional neural networks (CNNs) and early transformers. The comparison of these methods shows that they have essential discrepancies in the capability of extracting features, spatial generalization, and computational efficiency, and overall performance in fault detection tasks.

CNNs are good at extracting local features, which take advantage of convolutional filters to detect edges, offsets and other fault discontinuities in seismic data. Their hierarchical structure supports the low level layers to identify the simple patterns like edges or little amplitude variations whereas the high level layers identify more complicated structural patterns. This hierarchical learning renders CNNs especially useful in the identification of faults at all scales when operating with or without multi-scale architectures or encoder-decoder architectures. The CNNs, however, are not as aware of global context like they could be, that is, they might not detect faults which are of large spatial scale without further mechanisms, e.g., larger receptive fields, or multi-scale features.

Alternatively, transformer models make use of self-attention mechanisms to learn long-range interactions in seismic volumes. This capability allows transformers to take into account remote seismic characteristics in predicting the fault locations, and is especially beneficial in finding continuous faults or intricate web of interacting discontinuities. Preliminary research, including transformers, could be used in tandem with CNNs to offer global context awareness and, therefore, enhance the identification of subtle or spatially spanning faults. The application of transformers however demands large datasets and more computing power and therefore is more difficult to use in a limited seismic dataset scenario.

The trends of performance of studies depict that CNNs are always superior to the traditional edge and attribute-based approaches, and their precision and recall is high in both 2D and 3D seismic volumes. Multi-scale CNNs also enhanced the level of detection accuracy because it was able to identify both small and large faults. Transformers, which are not used as often at the current stage, demonstrated potential in capturing larger fault structures especially when used in combination with CNN features to create hybrid structures. The combination of CNNs and transformers enables the models to exploit the local and global context to achieve the best fault detection.

Deep learning models have also been demonstrated to be integrated with seismic attributes. CNNs and transformers can more effectively discriminate between fault related discontinuities and non fault related changes in amplitude when coherence, curvature or semblance attributes are added as a supplementary input channel. Multi-scale analysis also enhances strength such that models can represent minor discontinuities in addition to disruptions that are more evident.

Even with such developments, CNNs as well as transformers have major challenges. The limitation of this is that labeled 3D seismic volumes were not available which limited the ability to model, train and generalize. In many cases, data scarcity requires augmentation methods, transfer learning, or artificial data to be used to obtain a reasonable level of performance. Moreover, there is an issue of interpretability, although CNNs offer some visualization of trained feature maps, the dynamics of deep learning models, especially transformers, are still not well understood. Lastly, transferability to other basins or geological contexts can be difficult because of the differences in seismic acquisition parameters, lithology, and structural complexity and sometimes it may be necessary to fine-tune or re-train models to new data.

Table 3 provides a comparative summary of CNN and transformer-based methods from studies, highlighting datasets, reported accuracy, and the main pros and cons of each approach.

Table 3. Comparative summary of CNN vs. transformer-based fault detection methods

Method	Dataset	Accuracy	Pros	Cons
CNN	3D seismic volume	High	Efficient local feature extraction, robust multi-scale detection	Limited global context
Multi-scale CNN	3D seismic volume	High	Captures small and large faults simultaneously	Computationally intensive for deep networks
Transformer	2D/3D seismic slices	Moderate-High	Captures long-range dependencies, effective for continuous faults	High data requirement, computational cost
Hybrid CNN + Transformer	3D seismic volume	High	Combines local and global feature extraction, improved accuracy	Complex architecture, requires large dataset

Generally, CNNs offer a robust and computationally suitable framework to automated fault detection, as it is excellent in local feature extraction and multi-scale analysis. Transformers provide the complementary functionality of being able to capture more structural patterns, however, their use was restricted by data and computational limits. CNNs and transformers Hybrid architectures that combine the two will be a future direction of further work, in order to balance between local and global learning of features to enhance fault detection performance.

5. Challenges and Future Directions

Although there has been a major advance in the deep learning applications in detecting seismic faults, there are a number of challenges that restrict it to large scale adoption and operational assimilation. Among the most significant ones, one may distinguish the lack of data, specifically the unavailability of publicly accessible and label-dense 3D seismic volumes. The models of deep learning, particularly deeper CNNs and transformer-based models need large annotated datasets to reach a stable generalization. Seismic fault labelling is, however, not fast as expert interpreters have to identify discontinuities manually in thousands of inline and crossline cuts. Consequently, most research makes use of synthetic datasets, 2D subsets or semi-automated interpretations that all limit the variety and representativeness of fault patterns learnt by the model. To handle the problem of data scarcity, it will be necessary to increase open datasets, launch labeling programs, and develop faster labeling tools.

The second difficulty is the optimization and architecture of hybrid CNN+Transformer models that had massive concept potential but had less development. CNNs have been shown to be very useful in extracting local features like small offsets and amplitude discontinuities whereas transformers are useful in modeling longer-range interactions and are therefore useful in understanding longer fault planes or intricate intersecting fault networks. Other conceptual work, including ViT (Vision Transformer) and models that combine convolutional embeddings with attention layers, forms a basis to use in geophysical use in the future. The hybrid workflow could be applied in seismic fault detection wherein CNNs could be used to generate preliminary spatial feature maps, which are subsequently refined by transformer blocks that take into account the context. These hybrid systems would be able to give stronger predictions in different geological environments.

Semi-supervised, weakly supervised, and transfer learning methods can also be adopted in the future as a promising direction. This applies to semi-supervised learning which could use huge amounts of unlabeled seismic data, where consistency regularization, pseudo-labeling or contrastive learning could be used to enhance model performance. Weak supervision, in which the interpreters give crude labels or horizon-based structural directions in place of pixel-level fault annotations, may greatly cut down on labeling time. Transfer learning has other advantages especially in cases where the pre-trained models of one basin are utilized in new geological environments. Despite the fact that transferability is a difficult issue because acquisition parameters vary, and the structural complexity is different as well, the studies conducted in related fields indicate that the fine-tuning strategy to high-level features may enhance the generalization across basins.

Last but not least, there exists a strong possibility of closer integration with geophysical domain knowledge. Deep learning systems are black-box systems, which are not constrained by specific rules of geometry. Adding information about the system knowledge of the domain like structural regulations, fault dip anticipation or continuity of horizons may direct networks to geologically feasible interpretations. Physics-informed neural networks (PINNs), structure-consistency losses, or attribute-fusion methods are directions towards embedding expert knowledge in the field of geoscience as absolute parts of machine architectures. This kind of integration would not only enhance the interpretability and accuracy, but would also allow models to differentiate actual faults and noises, stratigraphic information, or artifacts of the acquisition.

6. Conclusion

Deep learning has substantially advanced the field of automated seismic fault detection, surpassing traditional attribute- and edge-based methods in accuracy, robustness, and scalability. CNNs have proven highly effective for extracting local and multi-scale features, enabling reliable detection of both subtle and prominent fault discontinuities in 2D and 3D seismic volumes. Meanwhile, transformer-based models and attention mechanisms have introduced new capabilities for capturing long-range geological context, improving the detection of extended, intersecting, or low-contrast faults. Although computational cost and the scarcity of annotated 3D datasets continue to limit the adoption of deep transformer architectures, hybrid CNN–Transformer frameworks represent a promising avenue for balancing local feature extraction with global structural reasoning.

Major challenges remain, including limited training labels, model interpretability, and transferability across basins with differing acquisition parameters and structural complexities. Future developments are expected to leverage semi-supervised learning, weak supervision, synthetic data generation, and geologically informed loss functions to mitigate these constraints. Integrating domain knowledge such as structural rules, horizon continuity, and dip trends into deep learning models will also be essential to improving both accuracy and geological plausibility. As the field progresses, deep learning methods are poised to become a cornerstone of next-generation seismic interpretation workflows, enabling faster, more consistent, and more comprehensive subsurface characterization.

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