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Artificial Intelligence for Automated Seismic Fault Detection: Revolutionizing Fault Identification and Improving Accuracy in Seismic Data Interpretation

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Abstract
Automated seismic fault detection using artificial intelligence (AI) represents a transformative advance in subsurface interpretation, offering unprecedented precision and efficiency in identifying fault networks. Traditional manual interpretation of seismic volumes is time-consuming and subject to interpreter bias, often leading to inconsistent fault mapping. This paper reviews state-of-the-art AI methodologies—such as convolutional neural networks, deep learning architectures, and unsupervised feature extraction—for automated fault identification. We evaluate the performance of these models on diverse geological settings, highlighting their ability to detect subtle discontinuities, leverage transfer learning across basins, and integrate multi-attribute seismic data. Case studies demonstrate significant improvements in fault continuity, reduced false-positive rates, and accelerated interpretation workflows. Challenges—including training data scarcity, network generalization across varying seismic quality, and the need for explainable AI—are critically discussed. Finally, we outline best practices for integrating AI-driven fault detection into existing geoscience workflows, propose strategies for model validation and uncertainty quantification, and identify future research directions aimed at real-time monitoring and adaptive interpretation. The review underscores AI's potential to revolutionize seismic fault mapping, improve reservoir characterization, and enhance decision-making in exploration and production.

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1. Introduction
1.1 Importance of Accurate Fault Mapping in Subsurface Characterization
Accurately mapping fault networks is critical to subsurface characterization because faults exert primary control on fluid flow, compartmentalization, and mechanical stability within reservoirs. Fault planes can either act as conduits—enhancing permeability along fracture corridors—or as barriers—sealing off compartments and trapping hydrocarbons. Without precise fault delineation, reservoir models may misrepresent pore connectivity, leading to erroneous predictions of production performance and recovery efficiency. Moreover, fault-induced stress perturbations influence geomechanical behavior, affecting wellbore stability and fracturing operations. In complex structural settings, such as thrust belts or deepwater fold-and-thrust systems, minor mispositioning of fault traces by even tens of meters can result in mis-drilled wells and costly sidetracks. Beyond hydrocarbon exploration, accurate fault maps support hazard assessment for CO_2 injection, geothermal exploitation, and seismic risk evaluation. Advanced subsurface workflows increasingly integrate high-resolution fault maps with dynamic flow simulators,

enabling improved history matching and production forecasting. Ultimately, fault mapping underpins decision-making from prospect maturation to field development planning, making its precision foundational for both economic success and operational safety.

1.2 Limitations of Manual Seismic Interpretation

Manual interpretation of seismic volumes remains the industry standard for fault identification, yet it is inherently labor-intensive and subjective. Interpreters must visually inspect hundreds of seismic inlines and crosslines, manually picking discontinuities that represent fault surfaces. This process can take weeks to months for a single field, delaying project timelines. Subjectivity introduces interpretive bias: two experts may diverge on subtle fault geometries in low signal-to-noise areas or near complex fold structures, leading to inconsistencies in fault network continuity. Fatigue and cognitive overload further degrade accuracy, especially when navigating large 3D surveys with varying seismic quality. Manual picks may inadvertently omit low-contrast faults or misclassify stratigraphic features as faults. Additionally, the manual workflow struggles to integrate multiple seismic attributes—such as coherence, curvature, and variance—into a unified interpretation, often relying on visual cross-comparison rather than quantitative analysis. As datasets grow in size and resolution, these limitations hamper scalability, reproducibility, and the ability to swiftly update fault models in response to new data.

1.3 Emergence of AI in Geophysical Workflows

Artificial intelligence has rapidly permeated geophysical workflows by automating pattern recognition and extracting complex features from multidimensional seismic data. Machine learning algorithms, especially deep convolutional neural networks (CNNs), excel at identifying fault-like discontinuities by learning hierarchical representations from labeled examples. Unsupervised methods, such as autoencoders or clustering techniques, can detect anomalous structures without extensive training labels, making them attractive in data-poor basins. The integration of seismic attribute volumes as multi-channel inputs to AI models enables simultaneous analysis of amplitude, coherence, and curvature features, improving fault delineation in challenging environments. Moreover, transfer learning allows pretrained networks—trained on one basin's data—to adapt quickly to new surveys, reducing the need for extensive retraining. AI tools seamlessly integrate into interpreter workstations, providing probability-weighted fault likelihood maps that expedite human review and QC. As AI matures, hybrid workflows combining automated detection with interpreter validation strike a balance between efficiency and expert oversight, positioning AI as a transformative enabler for more accurate and consistent seismic interpretation.

1.4 Objective and Scope of the Paper

This paper aims to provide a comprehensive review of artificial intelligence methodologies applied to automated seismic fault detection, evaluating their capacity to revolutionize fault identification and improve interpretation accuracy. The objective is to synthesize current advancements—from CNN architectures and unsupervised learning to transfer learning strategies—and assess their relative strengths in diverse geological contexts. Scope encompasses data preparation workflows, model training approaches, and integration techniques for incorporating seismic attributes into AI frameworks. Emphasis is placed on practical implementation: examining case studies of AI deployment in both synthetic and field datasets, analyzing performance metrics such as detection accuracy and false-positive rates, and highlighting best practices for integrating AI outputs into existing geoscience workflows. Limitations and challenges, including data scarcity, network generalization, and interpretability, are critically discussed. By surveying state-of-the-art developments, this review provides actionable insights for geoscientists seeking to adopt AI-driven fault detection in exploration and development projects.

1.5 Structure of the Paper

The paper is organized into five main sections. Section 2 examines AI methodologies for fault detection, detailing prevailing CNN architectures, deep learning variants such as U-Net and ResNet, and unsupervised learning techniques. Section 3 addresses data preparation and model training, covering seismic preprocessing, seismic attribute integration, ground-truth labeling, and transfer learning protocols. Section 4 evaluates performance through quantitative metrics and case studies, illustrating AI model benchmarking on synthetic and real-world datasets and discussing interpreter validation workflows. Section 5 outlines challenges, best practices, and future research directions, including strategies for addressing data limitations, enhancing model interpretability through explainable AI, and exploring real-time adaptive interpretation frameworks. Each section builds toward a cohesive understanding of AI's transformative impact on seismic fault mapping.

2. AI Methodologies for Fault Detection

2.1 Convolutional Neural Network (CNN) Architectures

Convolutional Neural Networks (CNNs) comprise a class of feedforward deep learning models characterized by stacked layers of convolutional filters that automatically learn hierarchical feature representations from raw input data (Sharma *et al*., 2019). At the core of a CNN is the convolutional layer, which applies multiple kernels across the input to generate feature maps sensitive to local patterns, such as edges or textures. Early layers capture simple features, while deeper layers encode complex abstractions. A pooling layer then subsamples these maps to reduce spatial dimensionality and enhance translation invariance (Oyedokun, 2019). Modern CNN architectures integrate batch normalization and rectified linear unit (ReLU) activations to accelerate convergence and mitigate vanishing gradient issues (Adenuga *et al*., 2019).

Architectures such as AlexNet, VGGNet, and GoogleNet pioneered deeper network designs by stacking numerous small convolutional filters (e.g., 3×3) and employing inception modules for multi-scale feature extraction. These designs informed subsequent domain-specific adaptations in seismic data analysis, where 2D slices of seismic volumes are treated akin to grayscale images. Omisola *et al*. (2020) demonstrated that customizing kernel sizes and dilation rates enables CNNs to capture both fine stratigraphic features and broader structural trends simultaneously. Furthermore, residual connections and skip pathways have been introduced to facilitate the training of very deep CNNs by allowing gradient flow around bottleneck blocks (ILORI *et al*., 2020). Such architectural refinements have improved the ability of

CNNs to generalize across varied reservoir settings, reducing overfitting when training data are limited. Overall, the evolution of CNN architectures underscores their adaptability to geophysical applications, where learning multi-resolution patterns is essential for reservoir characterization.

2.2 Deep Learning Models: U-Net, ResNet, and Variants

Deep learning architectures such as U-Net and ResNet introduced landmark improvements for pixel-level prediction and very deep network training, respectively. The U-Net model employs an encoder–decoder topology with symmetric skip connections that directly pass fine-grained features from encoding layers to the corresponding decoding layers (Ajuwon *et al*., 2020). This design ensures that spatial context is preserved while upsampling, making U-Net exceptionally effective for segmentation tasks where precise boundary delineation is critical. In reservoir characterization, U-Net variants facilitate the automatic mapping of reservoir facies and fault networks from seismic attribute volumes by learning from labeled well-log sections and interpreted horizons.

ResNet, on the other hand, enables the training of extremely deep networks by introducing residual blocks, where identity mappings bypass convolutional layers (Osho *et al*., 2020). This innovation mitigates vanishing gradients and allows direct gradient flow, supporting networks with hundreds of layers. In geophysical contexts, ResNet variants have been adapted to process 3D seismic cubes, capturing volumetric features through 3D convolutions and residual connections. These models excel in distinguishing lithology variations and fluid anomalies across large datasets.

Subsequent variants—such as ResNeXt and DenseNet—integrate grouped convolutions and dense connectivity to further enhance feature reuse and model compactness (Orieno *et al*., 2021). Hybrid models combining U-Net's segmentation prowess with ResNet's deep representation capacity have demonstrated improved performance in automating horizon tracking and seismic facies classification. Recent frameworks also incorporate attention mechanisms within U-Net and ResNet backbones, enabling the network to focus on salient subsurface features and suppress noise, thus refining interpretability and robustness (Daraojimba *et al*., 2021; Ajuwon *et al*., 2021).

2.3 Unsupervised and Semi-Supervised Feature Learning

Unsupervised feature learning leverages neural architectures—such as autoencoders and generative adversarial networks (GANs)—to extract latent representations of geophysical data without labeled examples. Autoencoders comprise encoding and decoding networks that compress input data into a low-dimensional bottleneck and reconstruct it, forcing the network to learn salient features (Onaghinor *et al*., 2021). In seismic applications, autoencoders can capture dominant waveform patterns and attenuate noise, facilitating subsequent clustering of subsurface facies. Variational autoencoders extend this paradigm by enforcing a probabilistic latent space, enabling data augmentation and uncertainty quantification in reservoir models.

GAN-based approaches utilize a generator–discriminator pair, where the generator synthesizes realistic seismic attributes and the discriminator learns to distinguish synthetic from real data. This adversarial training drives the generator to learn complex joint distributions of seismic amplitude, frequency, and phase variations. Oluwafemi *et al*. (2021) highlighted that GAN-derived features improve the detection of subtle seismic anomalies associated with fracture networks and fluid fronts.

Semi-supervised learning integrates limited labeled data with large unlabeled datasets to improve model generalization. Techniques such as consistency regularization—where models are trained to produce stable outputs under input perturbations—and pseudo-labeling—where confident model predictions on unlabeled data serve as additional training labels—have proven effective (Abayomi *et al*., 2021). In reservoir characterization, semi-supervised CNN frameworks have been shown to increase prediction accuracy of lithofacies distributions when well-log labels are sparse as seen in Table 1. Hybrid models combine supervised loss functions with reconstruction or adversarial losses to simultaneously learn discriminative and generative features (Abayomi *et al*., 2021; Nwani *et al*., 2020). These approaches reduce reliance on extensive manual interpretation, enabling rapid, scalable feature extraction across diverse seismic surveys.

Table 1: Summary of Unsupervised and Semi-Supervised Feature Learning Approaches in Seismic Data Analysis

Approach/Technique	Key Concepts & Architectures	Geophysical Applications	Advantages & Insights
Autoencoders & Variational Autoencoders	Encoding and decoding networks; probabilistic latent space (VAE)	Capture dominant waveform patterns; noise attenuation; data augmentation	Extract salient features, enable uncertainty quantification, facilitate clustering
Generative Adversarial Networks (GANs)	Generator–discriminator pair; adversarial training to learn data distributions	Synthesize seismic attributes; detect subtle anomalies (fractures, fluids)	Improve anomaly detection, learn complex joint distributions
Semi-Supervised Learning (e.g., Consistency Regularization, Pseudo-labeling)	Leverage both labeled and unlabeled data; stable outputs under perturbations	Lithofacies prediction with sparse well-log labels	Boosts model generalization and prediction accuracy
Hybrid Models	Combine supervised, reconstruction, or adversarial losses	Simultaneous discriminative and generative feature learning	Reduces manual interpretation, enables rapid scalable feature extraction

3. Data Preparation and Model Training

3.1. Seismic data preprocessing and attribute generation

High-resolution seismic sensors generate extremely dense wavefield data that require meticulous preprocessing to preserve signal integrity while attenuating noise. Initial steps include de-noising via spectral filtering and coherent noise suppression to isolate primary reflections (Bhola, Onyeka, & Clark, 2019). Adaptive deconvolution techniques are applied to compensate for source wavelet effects, enhancing temporal resolution and enabling the detection of thin beds less than one-quarter of the dominant wavelength. Following deconvolution, amplitude recovery corrects for geometric spreading and energy loss, standardizing reflection strengths across offsets (Agho *et al*., 2021).

Attribute generation transforms preprocessed seismic traces into quantitative measures—such as instantaneous phase, amplitude envelope, and spectral decomposition—that link directly to lithologic and fluid property variations. Instantaneous phase attributes reveal subtle structural features, including pinches and fractures, by highlighting continuity disruptions (Omisola *et al*., 2020). Envelope attributes emphasize high-energy events associated with gas-bearing sands or karst channels. Spectral decomposition yields frequency slices that correlate with porosity variations and depositional facies. Moreover, texture-based attributes—entropy and homogeneity—quantify lateral heterogeneity, critical for modeling permeability anisotropy in carbonate reservoirs (Ogunnowo *et al*., 2021).

Integration of geomechanical parameters—such as predicted pore pressure from passive seismic data—into attribute workflows enhances the discrimination of overpressure zones that may compromise wellbore stability (Adewoyin, 2021). By calibrating attribute-derived impedance models against predicted stress regimes, reservoir engineers can refine drilling plans and optimize completions. This preprocessing and attribute generation pipeline forms the bedrock of modern reservoir characterization studies.

3.2 Ground truth labeling and data augmentation

In seismic interpretation, ground truth labeling involves annotating seismic facies and event markers with known well-log or core information to train supervised machine-learning models. A common approach is to tie well markers—such as formation tops and fluid contacts—to seismic two-way time, generating labelled trace windows for lithology and fluid classification (Adenuga, Ayobami, & Okolo, 2019). Ensuring the accuracy of these labels requires rigorous depth–time conversion and iterative calibration against checkshot and VSP surveys.

Data augmentation addresses the scarcity of labelled seismic examples by synthetically expanding the training set. Techniques include adding controlled noise, time stretching, and amplitude scaling to replicate acquisition and processing variabilities (Daraojimba *et al*., 2021). Spatial augmentation, such as flipping and rotating 3D seismic cubes, preserves geological realism while increasing data diversity. Moreover, physics-informed augmentation—injecting synthetic faults, pinch-outs, or channel bodies into real data—enables models to learn rare but critical features (Adekunle *et al*., 2021).

Quality assurance of labels and augmented data relies on cross-validation against independent wells and blind picks. Metrics such as confusion matrices and area under the ROC curve quantify classification performance, guiding the refinement of label definitions. To mitigate bias, balanced sampling of classes—sandstone, shale, tight carbonates—is maintained through oversampling underrepresented facies (Hussain *et al*., 2021).

Recent studies also leverage generative adversarial networks (GANs) to produce realistic synthetic seismic sections conditioned on geological scenarios as seen in Table 2, offering a powerful augmentation tool without manual label injection (Hassan *et al*., 2021). Combined, these labeling and augmentation strategies underpin robust seismic facies classification and attribute inference workflows.

Table 2: Summary of Ground Truth Labeling and Data Augmentation in Seismic Interpretation

Key Aspect	Description	Techniques/Methods	Quality Assurance and Impact
Ground Truth Labeling	Annotates seismic facies and event markers using well-log or core data for supervised ML training.	Depth–time conversion, iterative calibration, checkshot and VSP survey alignment.	Cross-validation with independent wells and blind picks.
Data Augmentation	Expands training data by synthetically replicating acquisition and geological variability.	Noise addition, time stretching, amplitude scaling, flipping, rotating 3D cubes, GANs.	Preserves realism and increases model generalizability.
Physics-Informed Techniques	Simulates rare or critical features directly in real seismic data for advanced model learning.	Injection of synthetic faults, pinch-outs, channel bodies.	Enables models to detect subtle or infrequent geological features.
Performance Metrics	Measures and refines the effectiveness of labeling and augmentation strategies.	Confusion matrices, area under ROC curve, balanced sampling, oversampling.	Quantifies accuracy, mitigates bias, and guides workflow tuning.

3.3 Transfer learning and cross-survey model adaptation

Transfer learning enables the reuse of pretrained seismic interpretation models on new surveys with minimal retraining, saving time and data. A 3D convolutional neural network (CNN) trained on a large North Sea dataset for fault detection can serve as a base model for a Gulf of Mexico survey, adapting only the final classification layers (Afolabi & Akinsooto, 2021). Fine-tuning on a small set of labelled Gulf wells yields rapid convergence and high accuracy.

Cross-survey model adaptation tackles differences in acquisition parameters and subsurface geology. Domain adaptation techniques—such as adversarial training or discrepancy minimization—align the feature distributions of source and target seismic volumes (Ike *et al*., 2021). For example, a style transfer network can normalize amplitude and frequency content between surveys before interpretation, reducing misclassification of stratigraphic features.

Sequential transfer learning further improves performance by chaining pretrained models: first from a global training set, then from a regionally specific dataset, and finally from the local survey (Onaghinor *et al*., 2021). This hierarchical approach preserves broad seismic feature detectors while specializing on local lithologies and structural styles.

Lightweight model compression and knowledge distillation allow deployment of adapted models on edge devices during drilling, enabling real-time inference of lithology from downhole seismic while maintaining low latency (Akinade *et al*., 2021).

Overall, transfer learning and cross-survey adaptation frameworks dramatically reduce the data and compute requirements for seismic interpretation, promoting scalable, survey-agnostic workflows that accelerate reservoir characterization (Abayomi *et al*., 2021).

4. Performance Evaluation and Case Studies

4.1 Quantitative Metrics: Accuracy, Precision, Recall, and F1 Score

In evaluating seismic-based reservoir characterization workflows, quantitative metrics from machine learning—accuracy, precision, recall, and F1 score—provide objective measures of interpretive performance. Accuracy represents the ratio of correctly classified seismic events (e.g., true positives and true negatives) over all events; however, in data-imbalanced scenarios such as rare fracture detection, accuracy can be misleading (Adenuga *et al*., 2019). Precision quantifies the proportion of correctly identified positive events (e.g., actual hydrocarbon indicators) among all positive predictions, reflecting the confidence in flagged anomalies (Adekunle *et al*., 2021). Conversely, recall (sensitivity) measures the ability to detect all actual positive events, critical when missing a thin pay zone carries high economic risk (Adekunle *et al*., 2021). The F1 score, the harmonic mean of precision and recall, balances these metrics—particularly useful when classes are unbalanced, ensuring neither high precision nor high recall alone conceals poor overall performance (Abiola-Adams *et al*., 2021).

For example, in classifying amplitude anomalies indicative of gas saturation, a model with high precision but low recall may miss subtle anomalies, underestimating reserves (Adebisi *et al*., 2021). Optimizing the F1 score through threshold adjustment or cost-sensitive learning allows integration of domain-specific costs—misclassification of fluid types—into evaluation, thereby aligning metric optimization with reservoir risk management (Adekunle *et al*., 2021). These metrics guide the calibration of seismic interpretation algorithms and enable objective comparison across workflows, ultimately improving reliability in quantitative reservoir description.

4.2 Benchmarking on Synthetic and Field Data

Benchmarking seismic-based classification and inversion algorithms necessitates testing on both synthetic and field datasets to assess robustness and generalizability. Synthetic datasets, generated through forward modeling of wave propagation in known velocity and impedance contrasts, provide ground-truth controls for algorithm validation. Sharma *et al*. (2019) demonstrated how synthetic datasets calibrated with IoT sensor models enable systematic sensitivity analyses—varying noise levels, acquisition geometry, and subsurface heterogeneity—to quantify algorithmic stability under controlled perturbations. These experiments aid in establishing baseline performance metrics before field deployment.

In contrast, field data benchmarks incorporate real-world complexities: near-surface statics, irregular acquisition footprints, and variable environmental noise. Abayomi *et al*. (2021) outlined a cloud-based analytics framework that standardizes ingestion of diverse field data formats, enabling consistent preprocessing for benchmarking. Mgbame *et al*. (2020) highlighted challenges in data quality and access in underserved contexts—paralleling remote field surveys—underscoring the need for end-to-end benchmarking pipelines that include data validation and quality control modules.

Hybrid benchmarking approaches combine synthetic augmentation—embedding synthetic anomalies into field recordings—with pure field experiments to fill gaps in anomaly occurrence rates. Abisoye and Akerele (2021) employed such augmentation to assess anomaly detection models' resilience to low signal-to-noise ratios. Ajuwon *et al*. (2021) further suggested using blockchain-based data provenance tracking to ensure integrity and reproducibility of benchmark datasets across research teams. By integrating synthetic and field benchmarks, practitioners can iteratively refine seismic interpretation algorithms, ensuring reliable performance in exploration and development settings.

4.3 Workflow Integration and Interpreter Feedback Loops

Effective seismic interpretation workflows integrate quantitative algorithms into the interpreter's decision loop, enabling continuous improvement through feedback. Inclusive BI-platform design principles, as outlined by Abayomi *et al*. (2021), emphasize user-centered interfaces that allow geoscientists to interactively adjust algorithm parameters—such as classification thresholds or inversion regularization weights—and immediately visualize impacts on reservoir property maps. This fosters a collaborative environment where domain experts iteratively refine models based on geological plausibility.

Real-time analytics frameworks (Abayomi *et al*., 2021) support cloud-based deployment of seismic processing modules, ensuring that updates—driven by field observations or lab measurements—propagate through the interpretation pipeline without downtime. Daraojimba *et al*. (2021) illustrated how agile feedback loops in AI model development can be adapted for seismic workflows: interpreters validate model outputs against well logs, provide labeled corrections, and trigger automated retraining, thus improving model accuracy over time.

Onaghinor *et al*. (2021) demonstrated analogous frameworks in procurement, where predictive models are continuously calibrated with new transaction data—a concept transferable to seismic interpretation by feeding back drilling results and core measurements. Such closed-loop systems reduce turnaround and mitigate the risk of "model drift" when geological conditions differ from initial training data. Mgbame *et al*. (2020) identified barriers—such as limited connectivity in remote sites—and proposed lightweight, on-premise solutions to maintain feedback integration even in constrained environments. Integrating interpreter feedback loops with workflow automation ensures seismic interpretation remains adaptive, accurate, and aligned with evolving subsurface understanding.

5. Challenges, Best Practices, and Future Directions

5.1 Addressing data scarcity and quality variability

Effective AI-driven fault detection relies on large, representative seismic datasets, yet many exploration projects face limited or unevenly distributed data. To mitigate scarcity, practitioners can employ data augmentation techniques such as synthetic seismogram generation and elastic waveform simulation. By varying source-receiver geometry, noise levels, and geological parameters, augmented datasets capture a broader range of fault signatures, enhancing model robustness. Transfer learning offers another solution: pretrained networks on well-instrumented basins can be fine-tuned using smaller local surveys, allowing knowledge transfer of low-level features like discontinuity textures. Quality variability—due to acquisition footprints, multiple reflections, or acquisition gaps—can be addressed via adaptive preprocessing pipelines. Techniques like spectral whitening, wavelet denoising, and covariance-driven noise suppression standardize data inputs, ensuring consistent feature extraction. Moreover, active learning frameworks enable the model to request labels on the most ambiguous seismic patches, maximizing the value of limited interpreter time. By combining data augmentation, transfer learning, adaptive preprocessing, and active learning, AI workflows can overcome both scarcity and heterogeneity, leading to more reliable fault detection even in data-poor or noisy environments.

5.2 Explainable AI and interpretability concerns

Deep neural networks excel at pattern recognition but often operate as opaque "black boxes," raising interpretability challenges in critical exploration decisions. Explainable AI (XAI) techniques aim to bridge this gap by making model reasoning transparent. Saliency mapping highlights regions in input seismic volumes that most influence the network's fault predictions, enabling geoscientists to verify that detected discontinuities correspond to geological reality. Layer-wise relevance propagation and integrated gradients can trace output decisions back through individual filters, revealing which seismic attributes drive fault classification. Model agnostic methods such as SHAP (SHapley Additive exPlanations) quantify each input feature's contribution to the final detection score, clarifying the seismic amplitude, coherence, or curvature metrics most responsible for flagged discontinuities. Incorporating surrogate models—simpler decision trees approximating the deep network's behavior—further aids interpretability by summarizing complex decision boundaries in intuitive rules. By embedding XAI into the AI fault detection pipeline, interpreters gain confidence in automated results, can diagnose model biases, and maintain scientific rigor, ensuring AI outputs augment rather than obscure geological understanding.

5.3 Real-time fault monitoring and adaptive learning

Advances in computational architectures and cloud-based platforms now permit near–real-time seismic fault monitoring, crucial for drilling operations and dynamic reservoir management. Streaming workflows ingest new seismic or microseismic data continuously, feeding it into trained AI models that flag emerging fault activity or validate geosteering plans. To support adaptive learning, online training protocols update model weights incrementally as new labeled examples become available, preventing model drift and improving responsiveness to evolving subsurface conditions. Techniques such as continual learning employ memory replay buffers that retain representative historical samples, preventing catastrophic forgetting of earlier geological scenarios. Edge computing nodes deployed on production sites can run lightweight inference engines, triggering alerts when fault orientation or intensity metrics exceed safety thresholds. Integration with geomechanical models allows real-time AI outputs to feed into stress simulations, enabling proactive mitigation of induced seismicity risks. By coupling streaming data ingestion, online model updates, and edge inference, adaptive AI systems transform fault detection from a static interpretation task into a dynamic monitoring tool, enhancing operational safety and decision agility.

5.4 Roadmap for next-generation AI in seismic interpretation

The future of AI in seismic interpretation will be defined by increasingly integrated, physics-informed architectures and collaborative workflows. Next-generation networks will embed seismic wave propagation physics directly into model layers, constraining predictions to physically plausible fault geometries. Hybrid architectures combining data-driven deep learning with model-based inversion modules will enable seamless integration of well logs, geomechanical constraints, and machine learning outputs. Federated learning frameworks will allow multiple operators to collaboratively train models on proprietary datasets without compromising data privacy, expanding the diversity of training examples and improving generalizability. Advances in neuromorphic hardware and spiking neural networks promise orders-of-magnitude improvements in inference speed and energy efficiency, facilitating on-site, low-latency interpretation. Finally, integration with virtual and augmented reality platforms will provide immersive visualization of AI-detected fault networks, allowing geoscientists to interact with model outputs in three dimensions. This roadmap envisions a future where AI operates as a trusted, transparent, and physics-aware partner in seismic interpretation, driving higher accuracy and efficiency across the exploration lifecycle.

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