

Application of Artificial Intelligence and Machine Learning for Seismic Data Interpretation and Subsurface Characterization

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ABSTRACT

The integration of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized seismic data interpretation and subsurface characterization, shifting from labor-intensive manual workflows to automated, data-driven, and physics-constrained systems capable of handling massive, high-dimensional datasets. Supervised, unsupervised, and reinforcement learning paradigms now enable high-accuracy tasks including fault detection (via CNNs and GCNs), automated horizon picking (Vision Transformers and MDP models), seismic facies classification (U-Net, DeepLabV3+, FaciesMamba), and quantitative reservoir property prediction (porosity, permeability, shale volume) using FCNNs, Random Forests, and Physics-Informed Convolutional Neural Networks (PICNNs). Signal enhancement benefits from hybrid Transformer-GAN and collaborative denoising architectures that significantly improve signal-to-noise ratio while preserving subtle geological features. Physics-Informed Neural Networks (PINNs) and neural operators embed governing physical laws (wave equations, rock physics) into model training, ensuring consistency and generalization. Emerging trends include self-supervised learning, spiking neural networks, explainable AI (SHAP, Grad-CAM), and geo-foundation models for transfer learning across domains. These advancements deliver faster interpretation (up to 200×), reduced subjectivity, better uncertainty quantification, and improved decision-making in oil & gas exploration, earthquake early warning, and subsurface imaging. Challenges remain in labeled data scarcity, domain gaps, and model interpretability, but hybrid physics-ML frameworks position AI as a core enabler for precise, efficient, and reliable subsurface characterization in complex geological settings.

Keywords: Seismic Interpretation, Machine Learning In Geophysics, Physics-Informed Neural Networks (PINNs), Fault Detection, Horizon Picking, Seismic Facies Classification, Reservoir Characterization, Denoising GANs, Explainable AI (XAI), Subsurface Imaging, Neural Operators, Full-Waveform Inversion

Introduction

The evolution of seismological studies has historically followed a trajectory from manual observation and empirical derivation toward increasingly complex statistical modeling. Traditionally, the detection, analysis, and prediction of seismic events relied on classical statistical models and the subjective expertise of manual

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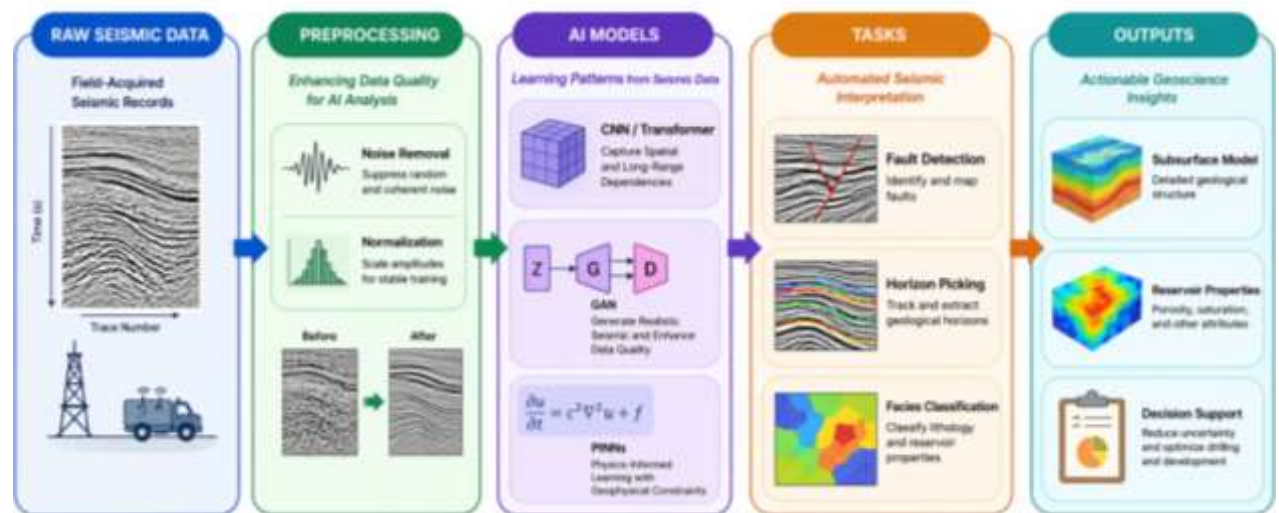
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interpreters (Plevris, 2024). However, the modern geophysical landscape is characterized by an unprecedented surge in data volume and complexity, driven by global sensor networks and higher-resolution acquisition technologies (Jiang et al., 2022). This shift has necessitated a transition toward more efficient, adaptive, and automated approaches, primarily through the integration of artificial intelligence (AI) and machine learning (ML) (Kharita et al., 2025). These technologies have emerged as transformative forces, enhancing the precision and depth of seismic data analysis while reducing the time-intensive nature of conventional workflows (Sousa et al., 2023). As shown in Figure 1, modern pipelines combine data preprocessing, deep learning models, and geological interpretation into a unified automated framework.

Figure 1: AI-Driven Seismic Interpretation Workflow

From Raw Seismic Data to Geoscience Insights



The Paradigm Shift in Geophysical Interpretation Frameworks

The integration of AI into geophysical workflows represents more than a mere computational upgrade; it is a fundamental paradigm shift in how subsurface information is extracted and utilized (Adler & Oktem, 2017). Traditionally, geoscientists relied on time-intensive manual interpretation for tasks such as fault detection, horizon picking, and facies classification. These processes were often subjective and constrained by the limits of human pattern recognition in high-dimensional datasets (Bergen et al., 2019). The emergence of AI has been inspired by parallel advancements in other high-stakes domains, such as financial modeling and credit automation, which similarly depend on robust pattern recognition and probabilistic forecasting (Dramsch, 2020).

Contemporary issues in seismology ranging from earthquake early warning (EEW) and phase picking to ground-motion prediction and seismic tomography now leverage AI-driven algorithms to provide more reliable forecasts and structural imaging (Kong et al., 2019). This transformation is particularly evident in the oil and gas sector, where AI optimizes reservoir characterization and reduces interpretation time, thereby lowering the financial risks associated with subsurface exploration (Di et al., 2018).

Table 1. Technical Impact of AI/ML Enhancement on Seismic Interpretation Tasks

Interpretation Task	Traditional Methodology	AI/ML Enhancement	Technical Impact
Fault Detection	Manual picking on 2D/3D slices	CNN and GCN-based edge detection	Reduced subjectivity; rapid computation (Brito, 2025)
Horizon Tracking	Cross-correlation and attribute similarity	Vision Transformers and MDP models	Maintains continuity across discontinuities (Olutoki et al., 2024)
Facies Classification	Heuristic rules and handcrafted features	Deep encoder-decoders (U-Net, DeepLabV3+)	Captures complex, nonlinear geological patterns (Priyatno et al., 2025)
Property Prediction	Empirical rock physics and linear regression	FCNN, Random Forest, and LSTM networks	Higher precision in heterogeneous formations (Hussain et al., 2025)

Foundational Machine Learning Paradigms in Seismology

The application of machine learning in seismic workflows is typically stratified into three primary learning paradigms: supervised, unsupervised, and reinforcement learning. Supervised learning remains the most pervasive approach, particularly when high-quality labeled datasets often calibrated from well logs or core samples are available (Wrona et al., 2018). These models are trained to map seismic signatures to specific geological labels, such as lithology types or structural discontinuities (Beroza et al., 2021).

Unsupervised learning, conversely, is critical in exploratory settings where labeled data is scarce. Techniques like self-organizing maps (SOM) and unsupervised clustering are used to detect hidden patterns and group multidimensional seismic attributes into geologically meaningful units. This approach is often mirrored in multi-attribute seismic clustering workflows used for prospect evaluation (Zhao et al., 2015).

Reinforcement learning (RL) represents an emerging frontier, particularly for dynamic and sequential decision-making tasks. In the context of drilling, RL algorithms enable real-time wellbore trajectory optimization by processing data streams to maximize hydrocarbon recovery (Kaur et al., 2020). For seismic interpretation, RL is being formulated through Markov Decision Processes (MDP) to automate horizon picking by imitating the behavior of a human interpreter who navigates across traces based on reward functions tied to attribute similarity and dip constraints (Shiah et al., 2021).

Signal Enhancement and Advanced Noise Attenuation

The reliability of any subsurface characterization is fundamentally limited by the signal-to-noise ratio (SNR) of the acquired seismic data. Traditional signal processing

techniques often fail to handle the nonstationary and complex noise patterns encountered in challenging geological regions (Beyer, 2025). AI-powered denoising has emerged as a superior alternative, capable of removing random and structured noise while preserving subtle geological features (Sheng et al., 2025).

Hybrid Transformer-GAN Architectures

The current state-of-the-art for seismic denoising utilizes hybrid architectures that integrate Convolutional Neural Networks (CNNs), Transformers, and Generative Adversarial Networks (GANs) (Mousavi & Beroza, 2022). CNNs are typically employed to extract local spatial features and perform multiscale analysis, which is essential for identifying reflections of varying frequencies (Saad & Chen, 2020). Transformers contribute by leveraging self-attention mechanisms to model long-range dependencies across the seismic volume, ensuring that global structural context is maintained during reconstruction (Yang et al., 2023).

GANs introduce an adversarial training framework consisting of a generator and a discriminator (Li et al., 2020). The generator aims to produce denoised data, while the discriminator evaluates the realism of the output against original clean signals. This approach avoids the common pitfall of CNNs over-smoothing where weak reflections are often lost in the denoising process (Wang et al., 2022). Experimental results using the STEAD (Stanford Earthquake Dataset) demonstrate that hybrid DAE-GAN (Denoising Autoencoder-GAN) models can significantly increase SNR and produce signals that are spectrally similar to the original high-quality recordings (Mousavi et al., 2019).

Collaborative and Self-Supervised Denoising

A major challenge in applying deep learning to geophysics is the scarcity of clean, well-annotated data from field surveys. To overcome this limitation, self-supervised learning approaches have been developed to reduce random noise without relying on synthetic training labels (MDPI, 2025).

Collaborative denoising networks (CDNs), based on blind signal separation, have demonstrated a strong ability to enhance the signal-to-noise ratio (SNR) of seismic data. For example, they can improve SNR from nearly imperceptible levels (e.g., 0.05 dB) to highly interpretable levels (e.g., 26 dB) (Effendi & T., 2025).

In addition, Spiking Neural Networks (SNNs) are being investigated as bio-inspired alternatives to conventional convolutional neural networks (CNNs). These models offer comparable denoising performance while providing greater efficiency in preserving temporal features of seismic signals (Antariksa et al., 2025).

Automated Structural Framework Construction

The construction of a structural framework is the bedrock of reservoir modeling and seismic interpretation. AI-driven automation has demonstrated the capacity to perform these tasks with up to 200x the speed of traditional methods (subsurfaceAI, 2025).

Convolutional and Graph-Based Fault Detection

Fault detection is increasingly treated as an image segmentation task using CNN architectures (Brito, 2025). These models are frequently trained on large volumes of

synthetic post-stacked amplitude maps where fault locations are precisely known (Luo et al., 2025). Recent advancements have introduced attention mechanisms into these networks, which reduce the total parameter count by half while improving precision, even in the presence of significant noise (Brito, 2025).

Beyond traditional CNNs, Graph Convolutional Networks (GCNs) offer a more time-efficient alternative for 3D seismic volumes. By representing data patches as k-nearest neighbor graphs, GCNs can classify faults with high accuracy by analyzing the seismic amplitude values in a parallel processing environment. Comparative analysis of different gradient boosting models (CatBoost, LightGBM) has also identified a clear hierarchy in performance for fault prediction (Lomax et al., 2024).

Table 2. Performance Comparison of Structural Interpretation Model Architectures

Model Architecture	Accuracy Metric (IoU/Precision)	Computational Demand	Primary Benefit
CNN + Attention	High (+0.6% IoU over standard)	Moderate	Robustness in noisy data (Brito, 2025)
GCN (Graph)	High	Low (Parallelized)	Faster than CNN architectures (Brito, 2025)
CatBoost / LightGBM	Very High	Low	Efficient for tabular attribute data (Brito, 2025)
Vision Transformer	Very High	High	Superior global spatial context (Olutoki et al., 2024)

Automated Horizon Picking and RGT Modeling

Horizon picking involves tracking continuous reflection surfaces across large seismic volumes. Vision Transformers (ViT) have shown great potential in this area, surpassing traditional trackers by effectively capturing multi-scale spatial patterns. A common approach for large-scale automation involves the estimation of Relative Geological Time (RGT) cubes (Olutoki et al., 2024). In an RGT cube, each point is assigned a scalar value that increases monotonically with depth; horizons can then be automatically extracted by picking contours within this volume (Zhang et al., 2025).

Seismic Facies Classification and Lithofacies Mapping

Seismic facies analysis focuses on identifying and grouping seismic patterns to interpret depositional environments and lithological properties. Deep learning has emerged as a powerful tool for this task, as it can capture the complex, nonlinear relationships that traditional heuristic rules often miss (Priyatno et al., 2025).

Advanced Neural Architectures for Facies Analysis

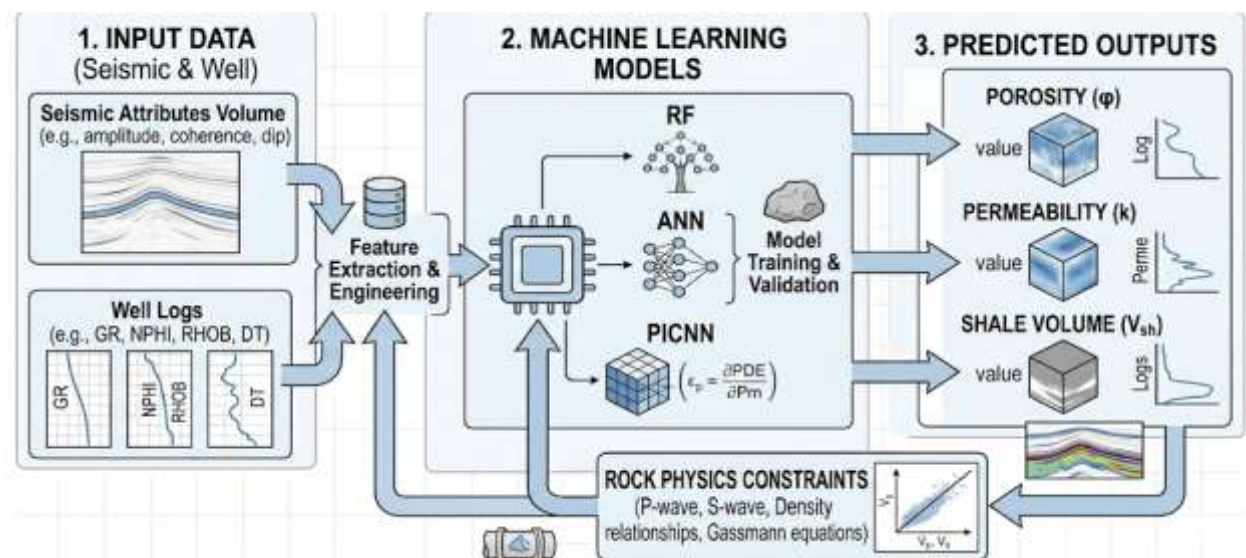
Current research focuses on deep convolutional architectures like U-Net and DeepLabV3+ for segmenting seismic facies (Wrona et al., 2021). In comparative

studies, DeepLabV3+ has shown greater stability and slightly higher training performance than U-Net, achieving validation accuracies exceeding 97%. However, these vision-based models can be overparameterized and computationally expensive (Zeng et al., 2022). To address these limitations, architectures like FaciesMamba have been introduced, utilizing structured state space models to significantly reduce the parameter count while achieving state-of-the-art performance (Zhang et al., 2024).

Quantitative Subsurface Characterization and Property Prediction

The ultimate objective of seismic interpretation is often the quantitative prediction of reservoir properties such as porosity, permeability, and shale volume (Hussain et al., 2025). AI-driven models enable accurate prediction of reservoir properties by integrating seismic and well log data, as illustrated in Figure 2.

Figure 2: AI-Based Reservoir Property Prediction Workflow



Deep Learning for Petrophysical Modeling

Modern workflows for reservoir property prediction commonly employ Fully Connected Neural Networks (FCNN), Random Forests (RF), and K-Nearest Neighbors (KNN) to map multidimensional seismic attribute data directly to petrophysical properties (Ahmad et al., 2022).

Studies conducted in offshore Malaysia have demonstrated that artificial neural network (ANN) and Random Forest (RF) models can achieve high predictive accuracy, with coefficient of determination (R^2) values reaching up to 0.95 for parameters such as porosity and shale volume (Abdulmutalib et al., 2025).

A key advancement in this field is the development of Physics-Informed Convolutional Neural Networks (PICNNs) (Sun et al., 2023). Unlike conventional convolutional neural networks (CNNs), PICNNs integrate petrophysical domain knowledge directly into the loss function. This approach ensures that predicted reservoir properties remain consistent with established rock physics relationships, thereby improving both model reliability and physical interpretability (Karpatne et al., 2021).

Table 3. Predictive Performance of AI Algorithms for Key Reservoir Properties

Reservoir Property	Algorithm Preference	Achievement (R2)	Key Input Attributes
Porosity (ϕ)	RF, ANN, PICNN	0.95 - 0.965	Impedance, GR, Neutron Log (Hussain et al., 2025)
Permeability (k)	RF, PICNN, KNN	0.80 - 0.947	FZI, Pore Throat Factor (Hussain et al., 2025)
Shale Volume (V_{sh})	RF, PICNN	0.908 - 0.95	Gamma Ray, SP, Density (Hussain et al., 2025)

Fluid Identification and AVO Inversion

Identifying fluid types distinguishing between hydrocarbons and water remains one of the most challenging aspects of subsurface characterization (Gong & Zhang, 2025).

AI-Driven AVO and Rock Physics

Recent innovations have replaced conventional shear-wave modeling with LSTM networks that autonomously learn nonlinear relationships among mineralogy, fluid distribution, and petrophysical parameters (Liu et al., 2020). This LSTM-enabled rock physics modeling, when combined with multi-azimuth angle gathers from Ocean Bottom Node (OBN) seismic data, significantly reduces fluid identification uncertainties (Di et al., 2018). Furthermore, semi-supervised learning methods with strong spatial feature constraints (SSFC-SSL) have been proposed for AVO inversion to improve lateral continuity (Sousa et al., 2023).

The Rise of Physics-Informed Neural Networks (PINNs)

Purely data-driven AI models often face challenges with limited generalization and poor physical consistency. Physics-Informed Neural Networks (PINNs) address these gaps by embedding governing physical equations as soft constraints within the neural network's loss function (Raissi et al., 2019).

Methodological Evolution and Seismic Modeling

The evolution of Physics-Informed Neural Network (PINN) methodology has advanced through several key developments, including adaptive optimization techniques, domain decomposition approaches such as extended PINNs (XPINNs), and the integration of hybrid numerical and deep learning frameworks.

In geophysical applications, the SeisPINN architecture has significantly reduced computational time for modeling tasks, decreasing it from approximately 48 hours to only 6 hours (Sansal et al., 2025). PINNs are particularly well-suited for full-waveform inversion (FWI) in semi-infinite heterogeneous media, as they can inherently satisfy absorbing boundary conditions without requiring explicit numerical implementation (Pakravan, 2024).

The foundational architecture of PINNs incorporates physical constraints into a composite loss function, expressed as:

$$L_{total} = L_{data} + \lambda_{phys} L_{wave_eq} + \lambda_{bc} L_{boundary}$$

where L_{wave_eq} represents the residual of the acoustic wave equation, typically

evaluated using automatic differentiation, and λ_{phys} and λ_{bc} are weighting coefficients that control the contributions of the physical and boundary condition terms, respectively (MDPI, 2025).

Theoretical Frontiers and Explainable AI (XAI)

As AI in geosciences matures, researchers are moving toward generalized frameworks like Neural Operators and Geophysical Foundation Models (GeoFM). The emergence of models like the Seismic Foundation Model (SFM) provides exceptional generalization abilities, allowing them to be fine-tuned for a wide range of downstream tasks (Sheng et al., 2025).

The "black box" nature of deep learning remains a barrier to adoption. Explainable AI (XAI) refers to methods like SHAP (Shapley Additive Explanations) and Grad-CAM that reveal how models reach their predictions (Sindhushree et al., 2025). In earthquake science, Grad-CAM analysis confirmed that PhaseNet's attention aligns with P- and S-wave arrivals, validating the model's behavior against geophysical intuition (Antariksa et al., 2025).

Table 4. Commonly Utilized Explainable AI (XAI) Techniques in Geoscience Applications

XAI Technique	Frequency in Literature	Functionality
SHAP	High (Identified in 35/44 Q1 articles)	Feature importance ranking; global/local interpretation (Antariksa et al., 2025)
LIME	High	Local surrogate modeling around specific predictions (Antariksa et al., 2025)
Grad-CAM	High	Visualizing network attention in image-based models (Antariksa et al., 2025)
Partial Dependence Plot	Moderate	Visualizing single attribute impacts on predictions (subsurfaceAI, 2025)

Conclusion

The application of Artificial Intelligence and Machine Learning has fundamentally transformed seismic data interpretation and subsurface characterization from subjective, time-consuming manual processes into precise, scalable, and automated workflows. By leveraging CNNs, Vision Transformers, GANs, and hybrid architectures for fault detection, horizon tracking, facies classification, denoising, and petrophysical property prediction, these technologies achieve superior accuracy, dramatically reduce interpretation time, and minimize human bias. The incorporation of physical constraints through Physics-Informed Neural Networks (PINNs), rock physics modeling, and multi-objective loss balancing ensures predictions remain geologically consistent while addressing challenges like data scarcity and the sim-to-real gap. Advances in self-supervised learning, spiking neural networks, and explainable AI further enhance model reliability, transparency, and generalizability. As geo-foundation models and neural operators mature, the field is moving toward truly multimodal, transferable systems capable of real-time analysis across diverse

datasets. Continued integration of domain knowledge with cutting-edge AI will be essential to unlock deeper insights into complex subsurface structures, optimize resource exploration, improve seismic hazard assessment, and support sustainable energy transitions. Ultimately, AI/ML-driven seismic interpretation stands as a cornerstone of modern geophysics, promising more efficient discovery, reduced exploration risks, and enhanced understanding of the Earth's subsurface.

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