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Application of Artificial Intelligence in the Identification and Characterization of Fracture–Cavity Carbonate Reservoirs

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Abstract

Carbonate reservoirs are among the most important carriers of global hydrocarbon resources. However, the accurate identification and quantitative characterization of their core storage space—the fracture–cavity system—remain a long-standing global challenge in petroleum exploration and development. Over the past decade, rapid advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have provided transformative tools to address the characterization difficulties arising from the strong heterogeneity and multiscale nature of carbonate reservoirs.This review systematically summarizes the applications of AI technologies in the study of fracture–cavity carbonate reservoirs from 2015 to 2025. The geological and engineering backgrounds, as well as the necessity of introducing AI techniques, are first outlined. Taking technological evolution as the main thread, research progress is reviewed from traditional machine learning to deep learning and further to intelligent methods based on multimodal data fusion. The review focuses on key research directions, including intelligent identification of fractures and cavities, parameter prediction, three-dimensional modeling, and data integration, with an emphasis on methodologies and representative applications. Current challenges are discussed in depth from three core dimensions: data, models, and knowledge-driven constraints. Finally, future research trends are prospected, highlighting the path toward interpretable, strongly generalizable, high-fidelity, and fully integrated intelligent workflows.

Keywords

Artificial Intelligence; Carbonate Reservoirs; Multi-source Information Fusion.

1. Introduction

Carbonate reservoirs are characterized by the coexistence of complex pore–fracture–vug multiphase media. Their strong heterogeneity and anisotropy lead to highly irregular distributions of storage space and complicated fluid flow mechanisms (Zhang Chengsen et al., 2011; Liang Qimin et al., 2023). Traditional fracture–cavity characterization methods, such as core description, well-log interpretation, and seismic attribute analysis, rely heavily on expert experience. When dealing with massive, high-dimensional, and nonlinear datasets, these methods often suffer from low efficiency and limited accuracy, making it difficult to meet the demands of fine-scale exploration and efficient development. Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), offers novel solutions to these challenges owing to its powerful capabilities in data-driven modeling, complex pattern

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recognition, and high-dimensional nonlinear mapping (Al-Obaidani et al., 2024). By automatically extracting deep features and hidden patterns from multi-source heterogeneous data—including seismic, logging, core, and production data—AI has driven a paradigm shift from “qualitative interpretation” to “quantitative prediction,” from “local description” to “three-dimensional modeling,” and from “static characterization” to “dynamic forecasting.” Studies over the past decade have demonstrated that, under complex geological conditions, AI-based methods significantly outperform many traditional approaches in fracture–cavity identification (Zongjie Li et al., 2024), marking the transition of this field into a new stage of deep integration, refinement, and intelligence.

During this evolution, the application of AI technologies has progressed from shallow machine learning models to deep neural networks and further toward specialized and integrated frameworks. Early studies primarily employed classical supervised learning algorithms—such as support vector machines (SVM), random forests (RF), gradient boosting decision trees (GBDT), and multilayer perceptrons (MLP)—for fracture identification, lithology classification, and preliminary prediction of porosity and permeability based on well-log data (Kouassi et al., 2023; Pei et al., 2022). These works demonstrated the potential of data-driven models but showed limited capability in characterizing complex fracture–cavity structures. With advances in computational power and algorithmic theory, deep learning has become dominant. Convolutional neural networks (CNNs) and U-Net architectures have been widely applied to the automatic identification and quantitative extraction of fractures and vugs from image logs and core images (Zongjie Li et al., 2024), while recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) networks, have been used to process sequential well-log data and capture fracture–cavity development patterns (Liu B. et al., 2023). Current research trends emphasize specialization, lightweight design, and data fusion. Improved YOLO-series algorithms have enhanced both the accuracy and efficiency of fracture–cavity system detection (Feng X. et al., 2024). Generative adversarial networks (GANs) and variational autoencoders (VAEs) are increasingly adopted for data augmentation and high-resolution reconstruction (Yuslandi et al., 2019). Meanwhile, physics-informed neural networks (PINNs) and multimodal deep learning frameworks aim to integrate physical equations, geological constraints, and multi-source information, thereby improving model generalization, interpretability, and the comprehensiveness of reservoir characterization (Ketineni et al., 2015; Hussein S., 2025).

Table 1. Applications of Artificial Intelligence in Fracture–Cavity Identification of Carbonate Reservoirs

Stage	Key Technologies	Application Areas	Representative Studies
Early exploration	Support vector machines, random forests, multilayer perceptrons	Fracture identification, lithology classification, preliminary parameter prediction	Kouassi et al., 2023; Pei et al., 2022
Advanced development	CNN,U-Net,LSTM,RNN	Image log and core image recognition, sequential data modeling	Zongjie Li et al., 2024; Liu B et al., 2023
Frontier breakthroughs	YOLO series, GAN, PINN, multimodal fusion	Fracture–cavity system localization, data augmentation, physics-constrained modeling, multi-source integration	Feng X et al., 2024; Ketineni et al., 2015; Hussein, 2025

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2. Characteristics and Challenges of Fracture–Cavity Carbonate Reservoirs

2.1. Characteristics of Fracture–Cavity Carbonate Reservoirs

Carbonate fracture–cavity reservoirs are characterized by extreme complexity and pronounced heterogeneity, making their accurate characterization a central challenge in hydrocarbon exploration and development (Wang Yan et al., 2023). These reservoirs are not simple porous media but rather a "multiphase medium" system in which macroscopic vugs, microscopic pores, and fractures of various scales coexist (Wu Yunlong et al., 2025). Their highly irregular spatial structures result in dramatic variations in storage capacity and fluid flow properties over short distances, leading to exceptionally complex fluid migration mechanisms (Jun Yao et al., 2016).

Table 2. Key Characteristics of Fracture–Cavity Carbonate Reservoirs

Characteristic	Specific Manifestation	Reference
Complex storage space structure	The storage space comprises a combination of pores, fractures, and vugs. For example, the Leikoupo Formation reservoirs in western Sichuan can be classified into pore-type, fracture–pore type, vug-type, and fracture–pore–vug type.	(TianH et al, 2019)
Extreme heterogeneity	Reservoir properties vary sharply in space. In the Yingshan Formation of the Tazhong area, strong heterogeneity and compartmentalization are observed, controlled by multiple karstification events and tectonic activities. Fracture-dominated, vug-dominated, cavern-dominated, and composite storage units can be distinguished.	(Pan, J.-G & Wei, 2012)
Multiscale and clustered distribution	Fracture–cavity development spans from millimeter to meter scale. Spatially, they often appear in clusters or aggregations rather than being uniformly distributed.	(Jun Yao, 2016)
Controlled by multiple geological processes	Mainly shaped by multi-stage paleo-karstification and subsequent tectonic fracturing. Paleogeomorphology, paleo-rivers, and fault zones control the spatial distribution of the fracture–cavity system.	(Zhang Ying,2018; Pan, J.-G & Wei, 2012)

2.2. Challenges in Characterizing Fracture–Cavity Carbonate Reservoirs

Geophysical Resolution and Identification Bottlenecks: Conventional seismic data have limited resolution, making it difficult to identify small fracture–cavity bodies with scales below 15 m. Such small features often appear in seismic profiles as "weak beads," low-amplitude anomalies, or chaotic reflections. The signals are subtle and easily masked by background noise. Advancing the detection scale from bead-level cavities (>20 m) to smaller and more concealed fracture–cavity assemblages is critical for improving recoverable reserves (Zhang Binxin et al., 2024).

Challenges in Multiscale Information Integration and Modeling: Fracture–cavity systems span multiple scales, from micro to macro. Single techniques—such as well logs, seismic surveys, or core analysis—only capture partial or scale-limited information, leaving "blind spots" in the dataset. The challenge lies in effectively integrating these heterogeneous, multiscale, and multi-type data to construct unified geological models. Purely data-driven or traditional interpolation methods struggle to accurately represent the spatial structure of fracture–cavity systems and their complex internal connectivity (Jun Yao et al., 2016).

Transition from Qualitative Identification to Quantitative Characterization: Current techniques can macroscopically identify fracture–cavity bodies using features such as bead-like reflections. However, exploration and development require precise quantification of geometric shapes, boundaries, internal fillings, porosity, permeability, and other parameters—tasks that remain highly challenging. For example, quantitatively predicting fracture density or vug size

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from seismic attributes while ensuring geologically reasonable results remains a frontier issue (Zhang Binxin et al., 2024).

Theoretical and Computational Challenges in Fluid Flow Simulation: Due to the highly irregular geometry of fracture–cavity networks, fluid flow mechanisms are complex, involving coupled flow regimes such as Darcy flow in fractures and free flow in large vugs. Traditional numerical simulation theories based on continuous porous media are generally inapplicable. Multi-scale hybrid simulation approaches, such as discrete fracture–vug–network (DFVN) models and equivalent medium models, are required, posing significant challenges in mathematical modeling and computational solution (Jun Yao et al., 2016).

Research on carbonate fracture–cavity reservoirs is transitioning from macroscopic qualitative identification to fine-scale characterization, intelligent integration of multi-source information, and geological-mechanism-constrained modeling. Future breakthroughs will depend on deeper interdisciplinary integration of geology, geophysics, reservoir engineering, and data science (Zhang Binxin et al., 2024; Jun Yao et al., 2016).

3. Core Research Focus

3.1. Intelligent Identification and Detection of Fracture–Cavity Systems

The intelligent identification and detection of fracture–cavity systems represent the most direct and widely applied area of AI in carbonate reservoir studies. Research focus has evolved from identifying individual fractures or vugs to comprehensive detection and classification of complex fracture–pore–vug systems.

Image-based identification: Convolutional neural networks (CNNs), U-Net, and similar models are employed to process image logs and digital core images, enabling automatic identification of fracture types (e.g., high-conductivity vs. high-resistivity fractures), extraction of fracture parameters (dip, strike, aperture), and quantification of vug morphology and spatial distribution (Zongjie Li et al., 2024). For example, dedicated deep learning models such as MFAPNet have been developed for core CT images to achieve quantitative characterization of fractures and vugs (Ma, Y. S. et al., 2023).

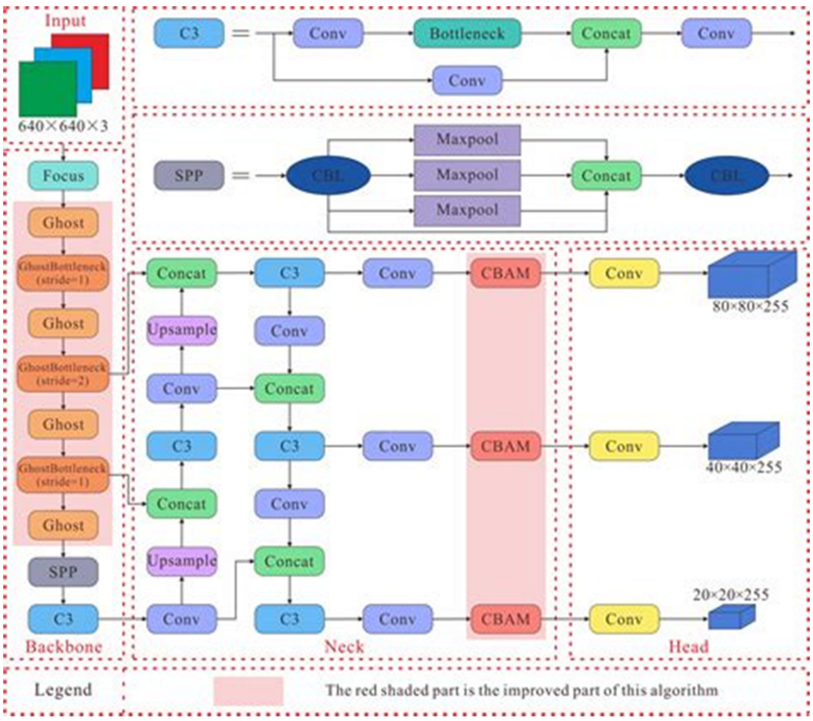

Figure 1. Network Architecture of the Improved 3D U-Net Model (Feng X. et al., 2024)

ISSN: 2688-8645

Well-log-based identification: Conventional well logs can be treated as one-dimensional time-series signals. Models such as 1D-CNN, LSTM, or Transformer networks are applied to automatically identify fracture–cavity-bearing intervals, reducing reliance on costly imaging logs (Al-Obaidani, H. S. et al., 2024).

Seismic-data-based identification: Two-dimensional and three-dimensional CNNs, U-Net, and related architectures are used to directly detect fracture–cavity anomalies, faults, and fracture zones from seismic volumes or multiple seismic attribute datasets. These approaches enable planar and spatial prediction of inter-well fracture–cavity structures (Zongjie Li et al., 2024; Feng X. et al., 2024).

3.2. Intelligent Prediction of Reservoir Parameters and Fluid Properties

Porosity and permeability prediction: AI models establish complex mapping relationships between well-log data, seismic attributes, and porosity–permeability parameters obtained from core analysis. Compared with traditional statistical methods, deep learning models handle nonlinearities more effectively, achieving higher prediction accuracy in highly heterogeneous areas (Hou, J. et al., 2022).

Quantitative prediction of fracture parameters: Fracture density, intensity, and porosity can be predicted using machine learning techniques. Multilayer perceptrons (MLPs) have been shown to perform effectively for such tasks. For instance, studies employing multi-source data fusion with MLP models have successfully predicted the spatial distribution of reservoir fracture parameters (Feng X. et al., 2024; Pei, J. et al., 2022).

Fluid identification and hydrocarbon potential prediction: By integrating well logs, seismic data, and geological information, AI models—such as random forests and deep neural networks—can distinguish reservoir fluid types (oil, gas, water) and evaluate reservoir productivity potential (Xiao Pengfei et al., 2020).

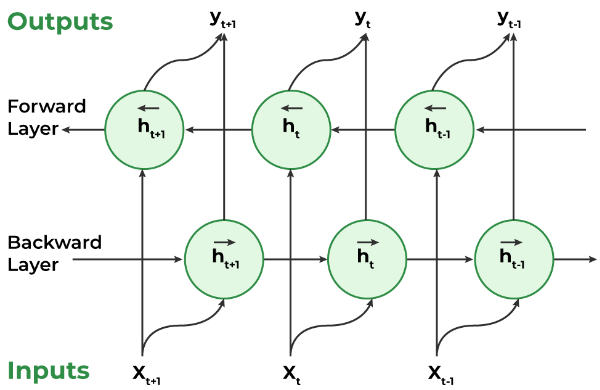

Figure 2. Bidirectional RNN – GeeksforGeeks (Mousavi S et al,2019)

3.3. Multi-Source Information Fusion and Integrated Characterization

Information from a single data source is limited, making multi-source data fusion a necessary approach to improve the reliability of reservoir characterization. AI plays a key role as both a "fusion engine" and a "decoder" in this process (Zhang Binxin et al., 2024).

Well–seismic joint intelligent characterization: Deep learning frameworks are constructed to simultaneously incorporate high-vertical-resolution information from well logs and lateral-continuous information from seismic data. This allows joint inversion or prediction of the three-dimensional fine structure of fracture–cavity reservoirs, achieving an integrated "point–plane–volume" representation (Zhang Binxin et al., 2024).

Multiscale data fusion: Multiscale neural networks are designed to handle data ranging from microscopic core thin sections to macroscopic seismic scales, enabling unified characterization

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of fracture–cavity systems from microstructure to macroscopic distribution (Ketineni, S. P. et al., 2015).

Integration of geological knowledge and data-driven models: Geological rules—such as depositional facies control and structural stress-field influence—are embedded into AI models as constraints, loss functions, or prior distributions. This "knowledge-enhanced" AI approach ensures that model outputs are not only data-driven but also geologically reasonable (Ketineni, S. P. et al., 2015).

4. Research Challenges

4.1. Data-Level Challenges

Data scarcity and imbalance: High-quality, labeled fracture–cavity data—especially "positive samples" containing hydrocarbons—are costly to obtain, resulting in small and imbalanced training datasets. Deep learning models tend to overfit under limited samples, leading to poor generalization (Li Guohui et al., 2015). Generative adversarial networks (GANs) can be used to generate synthetic data to alleviate this problem, but the authenticity of generated data must be carefully evaluated.

Heterogeneity and fusion difficulties of multi-source data: Seismic, well-log, core, and production data differ greatly in scale, resolution, and physical meaning. Designing effective network architectures and fusion mechanisms that allow AI models to truly understand and integrate heterogeneous information—rather than simply concatenating datasets—remains an unresolved challenge (Ketineni et al., 2015).

4.2. Model-Level Challenges

Model interpretability ("black-box" problem): Complex deep learning models operate opaquely, making it difficult for geoscientists to understand why certain predictions are made. This poses a significant barrier in high-stakes exploration decisions (Feng X. et al., 2024). Developing explainable AI (XAI) approaches—such as attention mechanisms and feature importance analysis—is a current research focus and urgent need.

Limited model generalization: Models trained in one field or under a specific depositional–diagenetic context often perform poorly when applied to areas with different geological conditions (Alatefi, S. et al., 2023). Carbonate reservoirs are highly diverse (e.g., reef–shoal bodies, karst fracture–cavity systems), with distinct formation mechanisms and controlling factors, necessitating AI models with strong cross-field, cross-type transfer learning or adaptive capabilities.

Physical consistency and geological plausibility: Purely data-driven models may produce mathematically optimal results that violate fundamental physical laws or geological knowledge—for example, predicting fracture orientations inconsistent with regional stress fields. Incorporating physical equations (e.g., flow and rock mechanics equations) and geological rules as hard or soft constraints into AI models—forming "physics-informed machine learning" or "geology-guided AI"—is key to improving model credibility and practical value (Ketineni et al., 2015).

5. Conclusion and Future Outlook

Over the past decade, artificial intelligence has deeply penetrated the study of fracture–cavity carbonate reservoirs, from identification and parameter prediction to 3D modeling, significantly improving automation, intelligence, and quantitative accuracy. Research focus has shifted from applying off-the-shelf models to developing specialized intelligent algorithms that

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integrate multi-source geological information. Future research is expected to advance along several directions:

Few-shot and self-supervised learning: To address the natural bottleneck of data scarcity, self-supervised learning can pretrain general feature representations on massive unlabeled datasets, followed by fine-tuning on limited labeled samples—a highly promising direction.

Hybrid intelligent modeling integrating physics and data: Combining numerical solutions from physical simulators with data-driven models can create "digital-twin"-level reservoir agents, enabling a closed-loop workflow from static characterization to dynamic simulation and prediction.

End-to-end integrated intelligent workflows: Developing AI platforms that cover data preprocessing, feature extraction, model training, 3D modeling, and risk analysis can advance fracture–cavity reservoir studies from "point intelligence" to "process intelligence."

Artificial intelligence is reshaping the paradigm of fracture–cavity carbonate reservoir research. Future success will depend on deep integration of geology, geophysics, and data science to tackle ultimate challenges in data, model, and knowledge fusion, ultimately achieving transparent reservoir understanding and intelligent hydrocarbon development

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