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Review

A Review of AI Applications in Unconventional Oil and Gas Exploration and Development

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Abstract: The development of unconventional oil and gas resources is becoming increasingly challenging, with artificial intelligence (AI) emerging as a key technology driving technological advancement and industrial upgrading in this field. This paper systematically reviews the current applications and development trends of AI in unconventional oil and gas exploration and development, covering major research achievements in geological exploration; reservoir engineering; production forecasting; hydraulic fracturing; enhanced oil recovery; and health, safety, and environment management. This paper reviews how deep learning helps predict gas distribution and classify rock types. It also explains how machine learning improves reservoir simulation and history matching. Additionally, we discuss the use of LSTM and DNN models in production forecasting, showing how AI has progressed from early experiments to fully integrated solutions. However, challenges such as data quality, model generalization, and interpretability remain significant. Based on existing work, this paper proposes the following future research directions: establishing standardized data sharing and labeling systems; integrating domain knowledge with engineering mechanisms; and advancing interpretable modeling and transfer learning techniques. With next-generation intelligent systems, AI will further improve efficiency and sustainability in unconventional oil and gas development.

Keywords: artificial intelligence; unconventional reservoir; geological exploration; production forecasting

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1. Introduction

The oil and gas industry faces growing challenges, such as unpredictable geological conditions, fluctuating market demand, investment risks, and stricter environmental regulations [1–5]. Traditionally, the industry has primarily relied on classical geological models and exploration techniques for the prediction and evaluation of oil and gas resources, while integrating production data analysis and reservoir modeling to optimize development plans for oil and gas fields. Geological engineers assess reservoir properties and hydrocarbon distribution through methods such as geological modeling and seismic exploration. Building on these assessments, petroleum engineers analyze production data to formulate specific development strategies, including injection-production design and fracturing plans [6–10]. Although these methods have achieved certain successes in the past, their limitations have become increasingly apparent with the growing demand for unconventional oil and gas

development, manifested in insufficient prediction accuracy, inefficient data processing, and high costs. To address these challenges, the introduction of artificial intelligence (AI) technologies with robust data processing and pattern recognition capabilities has become a key measure to enhance development processes and decision-making quality [11,12].

In recent years, AI technologies have been applied across multiple domains within the oil and gas industry, including exploration and production, drilling, equipment maintenance, and project management [13–21]. For instance, in geological exploration, AI has been applied to crack identification, lithology classification, reservoir property parameter prediction, reserve estimation, and sweet spot prediction, significantly improving the efficiency and accuracy of exploration [22–28]; in drilling and completion, AI is widely applied in drilling parameter optimization and rate of penetration (ROP) prediction, enhancing both the efficiency and safety of drilling operations [29–39]; in oil and gas field development, AI has been employed in production dynamics forecasting, production parameter optimization, reservoir numerical simulation, and assisted history matching, driving the efficient development of oil and gas while significantly reducing development costs [14,40–54].

As the industry transitions from conventional to unconventional reservoirs, new challenges have arisen. Choosing the right AI techniques is essential to address these challenges effectively. Furthermore, current research often focuses on specific areas, and both academia and industry have yet to develop a comprehensive understanding of the practical effects, applicability, and future development directions of these technologies in the development of unconventional oil and gas fields. A systematic analysis and summary of the existing applications of AI in unconventional oil and gas exploration and development are of significant importance for better addressing future challenges.

To delve deeper into the applications of AI in unconventional oil and gas exploration and development, this study comprehensively focuses on key issues in the development of unconventional hydrocarbon resources, encompassing geological exploration, reservoir engineering, production forecasting, hydraulic fracturing, enhanced oil recovery (EOR), and health, safety, and environment (HSE) management (as shown in Figure 1). For different application scenarios, we analyzed the specific applications, advantages, and limitations of various AI algorithms, and proposed future research directions and recommendations, aiming to promote the in-depth application of AI technologies in the development of unconventional oil and gas fields. Moreover, AIs have also been increasingly implemented in real-world industrial applications, where major oil and gas companies utilize AI-driven intelligent field management, predictive maintenance, and real-time production optimization to improve efficiency and reduce operational costs.

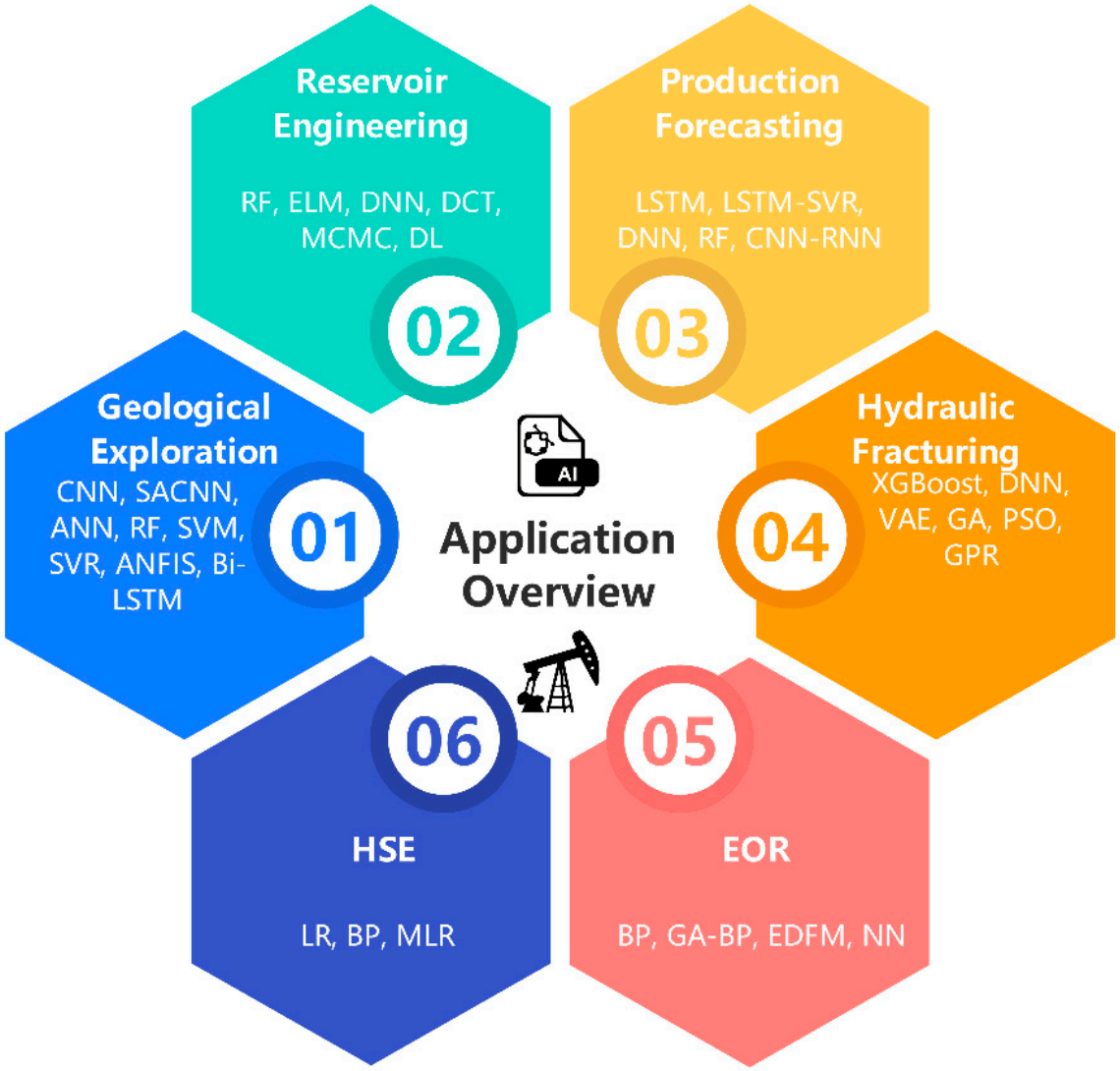


Figure 1. Overview of AI Applications in Unconventional Oil and Gas Exploration and Development.

2. From Conventional to Unconventional Oil and Gas Resources

2.1. Background to the Rise of Unconventional Oil and Gas

With the continuous growth of the global economy, energy demand has been steadily increasing. However, the proven reserves of conventional oil and gas resources have been growing at a slow rate, and many large oil fields have entered mature or declining phases, resulting in annual decreases in production [55]. This trend has compelled the energy industry and policymakers to reassess the future security of energy supply. Consequently, unconventional oil and gas resources have garnered increasing attention. These resources typically refer to oil and gas with commercial extraction potential found in shale and other low-permeability reservoirs. Due to their abundant reserves, unconventional oil and gas are progressively becoming key alternatives to conventional resources [56].

According to assessments, the global recoverable unconventional oil and gas reserves are approximately 44.21 billion tons and 227 trillion cubic meters, respectively, (as shown in Figures 2 and 3). These reserves encompass heavy oil, oil sands, tight oil, oil shale, shale gas, tight gas, and coalbed methane, significantly surpassing the reserves of conventional oil and gas resources [57]. The rise of unconventional oil and gas resources is attributed not only to their substantial reserves but also to breakthroughs in oil and gas development

technologies. In particular, innovations in horizontal drilling and hydraulic fracturing technologies have made previously difficult-to-extract resources economically viable [58].

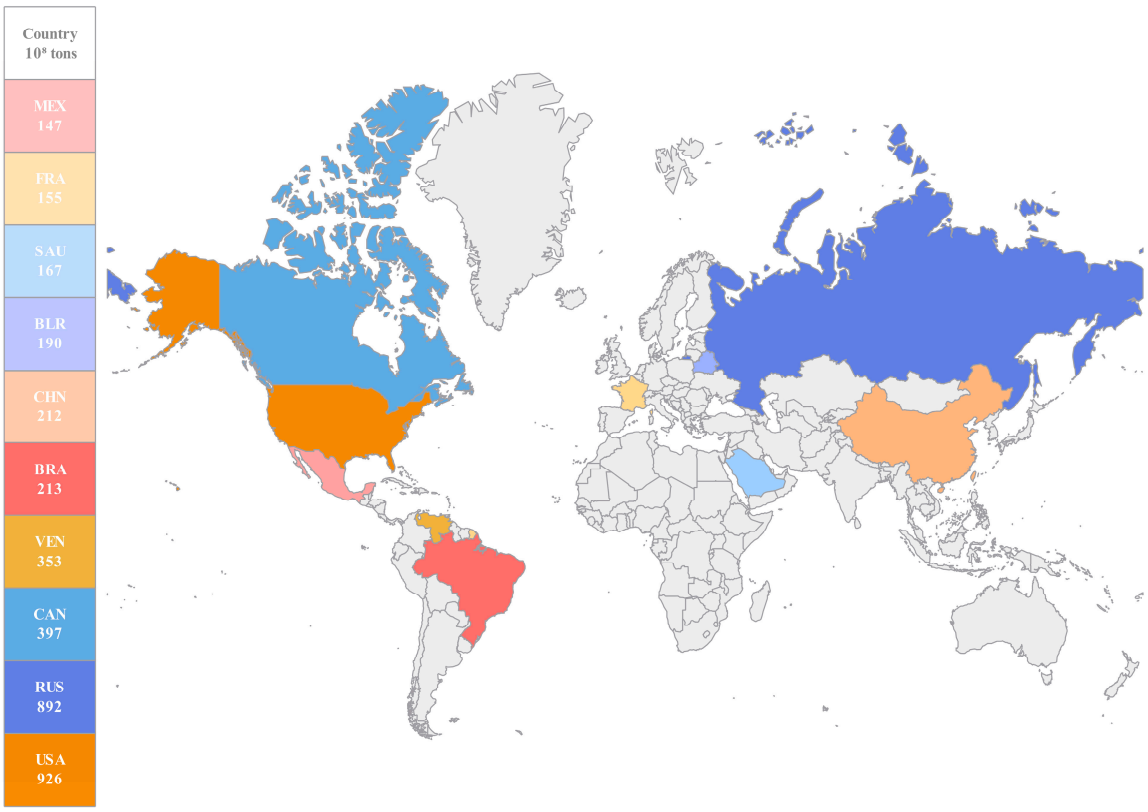


Figure 2. Map of global unconventional oil resources.

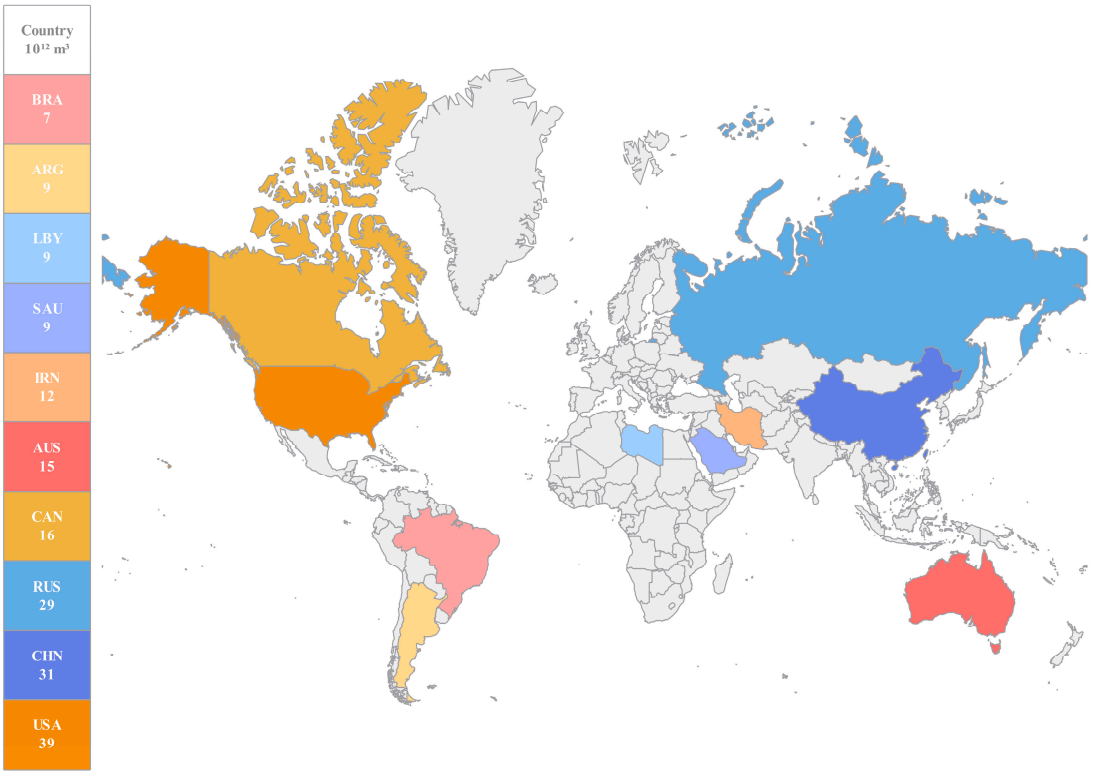


Figure 3. Map of global unconventional gas resources.

The development of unconventional oil and gas not only meets the growing energy demand but also has profound impacts on the global energy market landscape, playing an increasingly important role in the world economy and energy markets [59]. Countries such as the United States and China have incorporated the development of unconventional oil and gas into their national energy strategies, achieving significant economic benefits and technological advancements [60]. However, despite the numerous advantages brought by unconventional oil and gas development, it also faces multiple challenges, including technological complexities, environmental protection pressures, and high development costs [61]. Therefore, sustained technological innovation and policy support remain crucial for addressing these challenges and advancing the further development of unconventional oil and gas resources [62].

2.2. Challenges in the Development of Unconventional Oil and Gas

Specifically, the development of unconventional oil and gas faces the following primary challenges (as summarized in Figure 4).

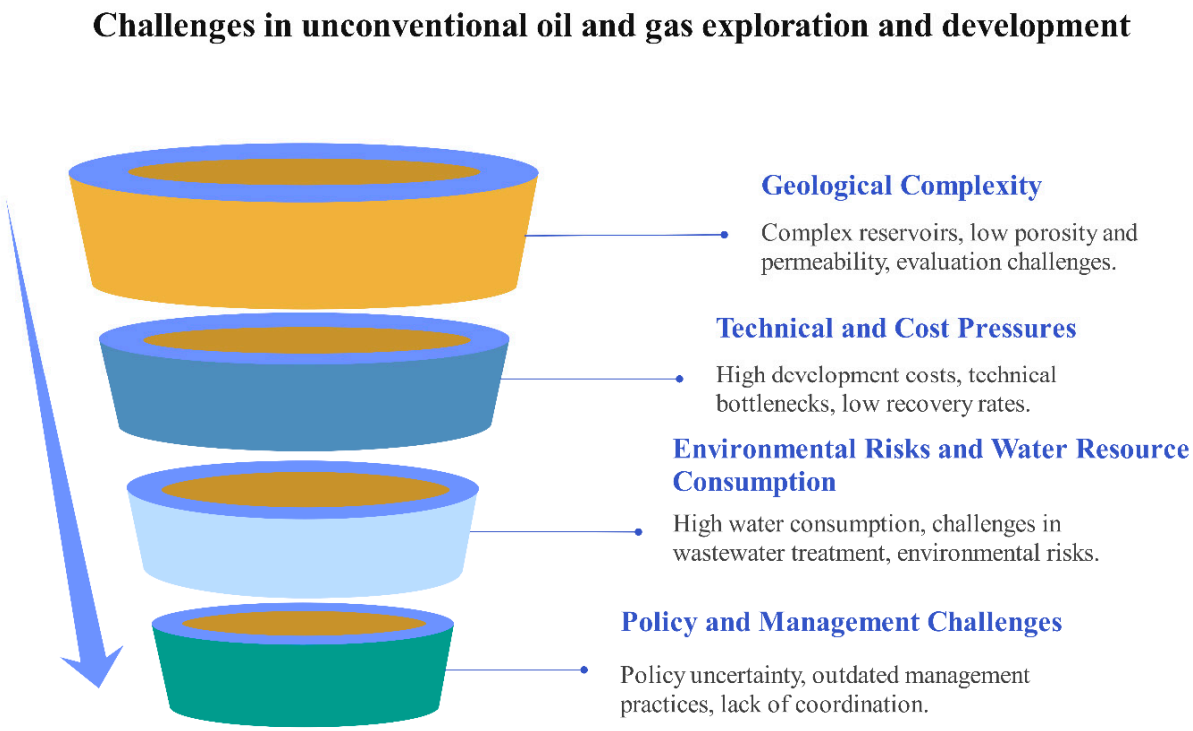


Figure 4. Main Challenges in the Development of Unconventional Oil and Gas.

Firstly, there are complex geological conditions. Unconventional reservoirs typically exhibit low porosity, low permeability, nanoporous media, complex lithology, and strong heterogeneity. These characteristics complicate the flow mechanisms of oil and gas, significantly increasing the difficulty of reservoir evaluation and production forecasting [63–65]. Additionally, the identification of "sweet spots" and the construction of high-precision geological models present further challenges, requiring in-depth geological understanding and innovative evaluation methods [66,67].

Secondly, there are technological and cost challenges. Traditional drilling and completion technologies are inadequate in meeting the demands of unconventional oil and gas development, necessitating the adoption of advanced techniques such as horizontal drilling and multistage hydraulic fracturing. However, these technologies encounter technical bottlenecks and high development costs. The success rate of drilling operations is relatively low, drilling cycles are prolonged, fracturing effectiveness is limited, and it is difficult

to improve oil and gas recovery rates [68,69]. High development costs and insufficient infrastructure constrain the economic viability of unconventional oil and gas, necessitating cost reductions through technological innovation and policy support [70].

Furthermore, environmental risks and water resource consumption are significant issues that must be overcome in the development of unconventional oil and gas. Hydraulic fracturing technology consumes large quantities of water and may impact the environment, raising public concerns about health and environmental safety [71,72]. Wastewater treatment and management present additional challenges, as the high salinity and numerous pollutants in the wastewater increase the difficulty of its treatment [73]. Therefore, the development of green and low-carbon extraction methods is essential to mitigate environmental impacts [74].

Finally, policy and management challenges restrict the large-scale economic development of unconventional oil and gas. Uncertainties in policy and regulatory environments, outdated management practices, and insufficient interdisciplinary collaboration need to be addressed through the combination of a "management revolution" and "technological innovation" [75]. Breakthroughs in technology, cost management, governance, and cognitive frameworks are necessary to fully unlock the economic development potential of unconventional oil and gas resources, thereby promoting the sustainable and low-carbon development of the oil and gas industry.

2.3. The Technological Transition from Conventional to Unconventional: The Necessity of Introducing AI Technologies

In response to the complexity and challenges of unconventional oil and gas development, the oil and gas industry has undergone significant technological innovation and transformation. Advanced geological and geophysical technologies, such as high-resolution seismic exploration and detailed geological modeling, have been widely applied in reservoir characterization and monitoring, significantly improving our understanding of complex geological conditions [76,77]. Advances in drilling and completion technologies, particularly horizontal drilling and multi-stage hydraulic fracturing, have dramatically increased the recovery rates of unconventional oil and gas [78,79]. Additionally, research into fluid flow in nanoscale pores has deepened our understanding of unconventional reservoir seepage mechanisms, providing theoretical support for optimizing development strategies [80–82].

However, traditional technologies still face limitations in addressing the various challenges of unconventional oil and gas development. Artificial intelligence (AI) technologies, with their powerful data processing and pattern recognition capabilities, have become the core driving force behind the advancement of unconventional oil and gas exploration and extraction technologies. Therefore, the shift from conventional to unconventional resources is not only a change in resource types but also a revolution in technological methods and approaches, with AI playing a critical role in this transformation.

3. The Applications for AI Algorithms in Unconventional Oil and Gas Exploration and Development

3.1. The Applications for AI in Geological Exploration

The application of artificial intelligence (AI) in unconventional oil and gas geological exploration provides new approaches to address challenges under complex geological conditions. Traditional methods often struggle with nonlinear, high-dimensional, and uncertain data. The introduction of AI technology enhances exploration accuracy and efficiency, making it an important research direction.

3.1.1. Prediction of Gas Probability in Reservoirs

Gas probability prediction plays a critical role in the exploration of unconventional oil and gas reservoirs. Traditional methods often fail to capture the complex nonlinear relationships between seismic data and reservoir characteristics. Yang et al. (2024) have proposed a method based on a Self-Attention Convolutional Neural Network (SACNN), combined with transfer learning and the use of Multi-Component Seismic Attribute Data (MSAD), to achieve a high-precision prediction of Gas Probability Distribution (GPD) in tight sandstone gas reservoirs (as illustrated in Figure 5) [83]. By incorporating self-attention mechanisms, the model enhances its focus on key features, achieving an R^2 of 0.9731 and significantly improving predictive accuracy.

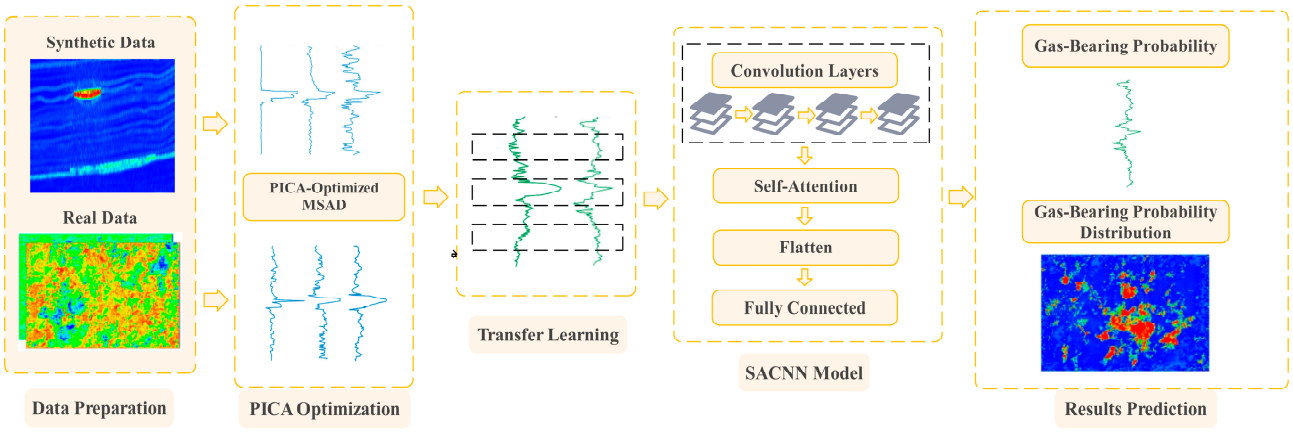


Figure 5. Prediction of reservoir gas distribution based on SACNN model [83].

Lin et al. (2020) have applied a Mutation Particle Swarm Optimization-Artificial Neural Network (MPSO-ANN) approach to optimize and select seismic data, further improving the precision of gas probability prediction [84]. Their study has demonstrated that the combination of intelligent optimization algorithms and neural networks effectively addresses high-dimensional data feature selection problems.

SACNN and MPSO-ANN models perform well in gas probability prediction, but they struggle with noisy seismic data, which affects their accuracy. Future research could explore models that integrate multi-scale feature extraction and adaptive denoising techniques to enhance prediction stability in complex geological settings.

3.1.2. Lithology Classification

Accurate lithology classification is essential for the identification and evaluation of unconventional reservoirs. Traditional classification methods are limited by their reliance on manual expertise and their inability to process large volumes of well-logging data. Zhu et al. (2020) used a one-dimensional convolutional neural network (1D-CNN) with an improved deep network structure to classify lithology from well-logging data [85]. The model they have developed effectively leverages the spatial features of well-logging curves, achieving a maximum Area Under the Curve (AUC) of 0.9107.

Moreover, Pang et al. (2024) have introduced a Spatiotemporal Network (STNet) that integrates the spatial and temporal information of well-logging data, achieving high-precision lithology classification with an accuracy of up to 96.83% [86]. These studies demonstrate the unique advantages of deep learning models in handling complex and multidimensional well-logging data.

While current models achieve high accuracy in lithology classification, challenges remain in identifying subtle differences between lithofacies categories, especially under

oversampling-enhanced data conditions. Future research could focus on developing refined categorical labeling systems tailored to regional lithofacies characteristics and incorporating few-shot learning techniques to reduce reliance on extensive labeled datasets.

3.1.3. Brittleness Index Estimation

The Brittleness Index (BI) is a critical parameter affecting hydraulic fracturing performance in unconventional reservoirs. Traditional BI estimation methods rely heavily on experimental testing, which is costly and inefficient. Kivi (2017) used an Adaptive Neuro-Fuzzy Inference System (ANFIS) combined with conventional well-logging data (GR, NPHI, RHOB, DT) to achieve a high-precision BI prediction, with an R^2 of 0.936 on the test set [87]. This model integrates the learning capabilities of neural networks with the reasoning power of fuzzy logic, effectively handling nonlinearity and uncertainty.

Additionally, Ore and Gao (2023) compared various models, including Gradient Boosting (GB), Support Vector Regression (SVR), and Neural Networks (NN), for BI prediction and found that SVR performed the best, achieving an R^2 of 0.87 [88]. This indicates that different machine learning models have distinct strengths in BI prediction, and model selection should be based on the specific characteristics of the data.

Although ANFIS and SVR models perform well in BI estimations, their robustness to complex lithological combinations and nonlinear feature variations is limited, particularly in high-pressure and high-temperature conditions. Future work could introduce physical constraint mechanisms to improve adaptability to extreme reservoir conditions.

3.1.4. Prediction of Total Organic Carbon Content

TOC content is a crucial indicator for evaluating shale gas reservoirs. Traditional TOC measurement methods are time-consuming and costly. Zheng and Wu (2021) have proposed a Fully Connected Deep Network (FCDN) model for TOC prediction using well-logging data (GR, RT, DEN, AC), achieving high accuracy with an R^2 of 0.89 and a Normalized Root Mean Square Error (NRMSE) of 0.044 [89].

Furthermore, Zhang et al. (2023) applied a Gradient Boosting Decision Tree (GBDT) model to analyze well-logging data for TOC prediction, achieving an R^2 of 0.9254 and a Root Mean Square Error (RMSE) of only 0.032 [90]. Their study highlights the advantages of ensemble learning models in handling nonlinear problems and avoiding overfitting.

While FCDN and GBDT models exhibit high accuracy in TOC prediction, significant prediction bias occurs in cases of insufficient input data (e.g., single-well data) or inconsistent multi-well data. Future research should focus on developing deep learning models that incorporate inter-well topological relationships to enhance multi-well collaborative prediction capabilities and improve the analysis of complex relationships between different well-logging curves.

3.1.5. Prediction of Geomechanical Parameters

Geomechanical parameters are critical for well completion design and hydraulic fracturing optimization in unconventional reservoirs. Nath and Asish (2022) utilized Bidirectional Long Short-Term Memory (Bi-LSTM) networks and Random Forest (RF) models to predict Shear Wave Slowness (DTS) and geomechanical parameters based on well-logging data [91]. The Bi-LSTM model effectively captured the temporal dependencies of well-logging data, significantly improving prediction accuracy, while the RF model achieved 99.9% accuracy in single-well predictions.

However, these models require significant computing power, making them less practical in resource-limited environments. Future studies could explore algorithm structure optimization and hybrid approaches to enhance cross-well prediction capability while re-

ducing computational costs, enabling efficient adaptation to multi-well and multi-regional geomechanical parameter predictions.

In addition, AI has other applications in unconventional oil and gas geological exploration, albeit less frequently studied but equally significant. For example, Ashraf et al. (2020) used UVQ and ACO algorithms to extract fault parameters from seismic attributes [92]; Mustafa and Tariq (2022) employed ANN and ANFIS to predict mineral composition [93]; Qian and He (2018) utilized SVM and fuzzy mathematics to predict sweet spot attributes [94]; and Zhu and Song (2022) applied NRF to generate missing well-logging curves, addressing data incompleteness issues [95].

To better understand the current applications of AI in unconventional oil and gas geological exploration, the progress of relevant research is summarized in Table 1.

Table 1. Applications of AI in Unconventional Oil and Gas Geological Exploration.

Reservoir Property Prediction and Gas Probability Prediction			
Reference	**Method**	**Input Parameters**	**Output Parameters**
[83]	CNN, TL	Seismic attributes	Gas probability distribution
[84]	ANN, MPSO	Seismic attributes	Gas probability distribution
[96]	MLP, RBF	Seismic attributes	Gas probability distribution
Lithology and Facies Classification			
Reference	Method	Input Parameters	Output Parameters
[97]	CNN	Well logging data	Reservoir classification
[98]	RF, SVM, XGB	NMR pore structure features, reservoir physical data	Reservoir classification
[99]	DNN, MAHAKIL	Well logging data	Lithology and fluid classification
[100]	RF, SVM, XGB	Well logging data	Lithofacies classification
[86]	STNet	Well logging data	Lithology classification
Brittleness Index Estimation			
Reference	Method	Input Parameters	Output Parameters
[88]	GB, SVR, ANN	Well logging data	Brittleness index
[87]	ANFIS	Well logging data	Brittleness index
[101]	FL, ANN, GA	Well logging data, mineral composition, rock mechanics	Brittleness index, TOC, Fracture index
TOC Content Prediction			
Reference	Method	Input Parameters	Output Parameters
[102]	ANN	Well logging data	TOC
[89]	FCDN	Well logging data	TOC
[103]	GWO, EN, ELM, SVR, MARS	Mineral composition	TOC
[104]	Metaheuristic, ELM, EN, SVR, MARS	Mineral composition	TOC
[105]	SSGCN	Well logging data	TOC
[106]	SVR	Well logging data	TOC
[90]	GBDT	Well logging data	TOC
Geomechanical Parameter Prediction			
Reference	Method	Input Parameters	Output Parameters
[97]	ANN	Well logging data	Vs, geomechanical parameters
[91]	Bi-LSTM, RF	Well logging data	DTS, geomechanical parameters
[107]	Bagging	Well logging data	Minimum horizontal stress (Shmin)
Others			
Reference	Method	Input Parameters	Output Parameters
[92]	UVQ, ACO	Seismic attributes	Fracture parameters
[93]	ANN, ANFIS	Well logging data	Quartz content, clay content
[94]	SVM, FL	Geological and seismic attributes	Sweet spot property prediction
[95]	NRF	Well logging data	Generation of missing logging curves

3.2. AI Drives Reservoir Engineering

Unconventional oil and gas reservoirs exhibit complex geological characteristics and fluid behaviors, making traditional reservoir engineering methods inefficient or insufficiently accurate in addressing these complexities. In recent years, the rapid development of AI technologies has provided new approaches and methodologies to overcome these challenges.

AI has demonstrated powerful capabilities in reservoir characterization and permeability prediction. Wang and Sharma (2021) utilized the Random Forest algorithm to predict oil saturation in offshore fields based on production data, assisting in reservoir characterization [108] (the workflow is shown in Figure 6). This approach effectively handled the complex geological conditions in highly fractured and heterogeneous reservoirs, significantly improving the accuracy of reservoir parameter predictions.

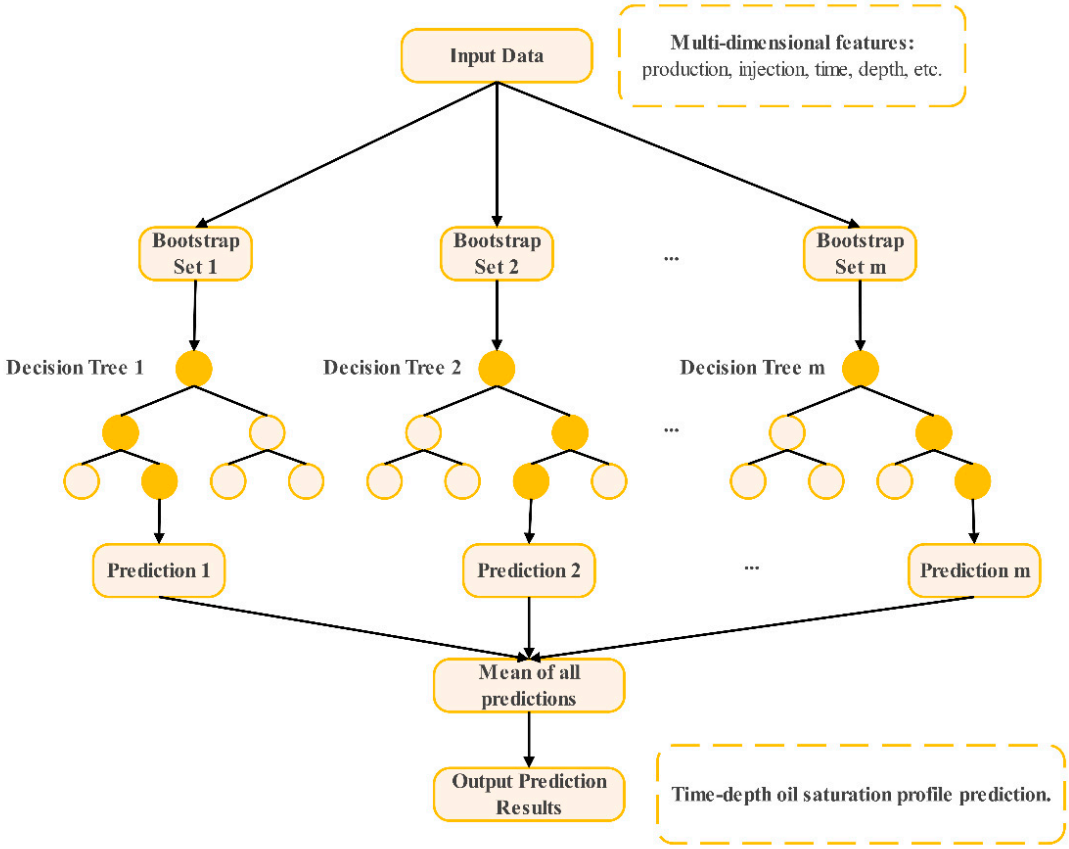


Figure 6. Workflow for Oil Saturation Prediction Using Random Forest.

Similarly, Liu et al. (2021) employed the Extreme Learning Machine (ELM) algorithm to characterize multivariate reservoir properties and successfully predicted key parameters such as lithofacies, porosity, clay content, and saturation [109]. Due to its fast training speed and strong generalization capability, ELM is particularly suitable for processing large-scale data, enabling real-time decision-making in reservoir engineering.

For permeability prediction in unconventional reservoirs, Li et al. (2023) proposed a model combining Discrete Cosine Transform (DCT) and Artificial Neural Networks (ANN) to achieve high-accuracy predictions for permeability in nanoporous materials such as shale [110]. The introduction of DCT effectively reduced data dimensionality, improved computational efficiency, and addressed the computational bottleneck of traditional methods in processing high-dimensional digital rock images.

Fang and Carcione (2024) applied Deep Neural Network (DNN) models to predict permeability in tight oil and gas reservoirs [111]. By incorporating multi-parameter inputs from well-logging data, the DNN model successfully captured complex nonlinear relationships, significantly enhancing permeability prediction accuracy. This provides critical technical support for the development of tight reservoirs.

AI methods have also demonstrated unique advantages in reservoir simulation and history matching. Wang and Sobecki (2019) developed a deep learning-based flash calculation module, which significantly accelerated gas–liquid phase equilibrium calculations in unconventional reservoirs [112]. Traditional flash calculations often face convergence difficulties under high capillary pressure conditions, while deep learning models provide high-quality initial values, improving both stability and efficiency.

Dachanuwattana et al. (2018) utilized a Markov Chain Monte Carlo (MCMC) method with surrogate models to assist in history matching for shale oil reservoirs [113]. The use of surrogate models reduced the computational cost of the MCMC method, overcoming the challenges of high computational demand and the non-uniqueness of solutions in traditional history matching. This approach improved both matching efficiency and prediction accuracy.

In summary, the application of AI in reservoir characterization, permeability prediction, reservoir simulation, and history matching not only enhances computational efficiency and prediction accuracy but also provides new methodologies for addressing complex geological and engineering problems. However, it is crucial to note that the performance of AI models heavily depends on data quality and the rational design of models. Future research should focus on exploring AI algorithms better suited to the characteristics of unconventional reservoirs, integrating physical models and domain knowledge to develop more robust and interpretable models, thereby supporting the efficient development of unconventional oil and gas resources. The relevant research findings are summarized in Table 2, which presents different AI methods used for reservoir engineering applications.

Table 2. Applications of AI in Reservoir Engineering.

Reference	Method	Input Parameters	Output Parameters	Resource
[112]	FCNN	Reservoir Conditions, Composition Data	Phase State, Component Concentration, Pc	Shale Gas
[113]	Proxy-based MCMC	Reservoir Properties	BHP, Production Error, Recovery Prediction	Shale Oil
[108]	RF	Production and Operational Data	Oil Saturation Profile (So)	Tight Oil
[109]	ELM	Elastic Attribute Data	Lithofacies, Reservoir Properties	Tight Sandstone Gas
[110]	DCT, ANN	Rock Image Features	Permeability	Shale Gas
[111]	DNN	Well Logging Data	Permeability	Ordos Basin Tight Oil

3.3. Applications of AI in Production Forecasting for Unconventional Oil and Gas

In the development of unconventional oil and gas resources, production forecasting plays a critical role in reservoir engineering and field development research. Traditional methods for analyzing production dynamics, such as reservoir numerical simulation, type curve analysis, decline curve analysis, and material balance methods, have been widely used in field production for decades [114]. However, due to the complexity of geological environments and the diversity of factors influencing dynamic production index predictions in unconventional reservoirs, these methods exhibit significant limitations.

Currently, a common approach involves the application of neural networks and other artificial intelligence algorithms, combined with deep learning models, to address the nonlinear and time-series characteristics of production data from unconventional reservoirs (the workflow of production forecasting is shown in Figure 7). These advanced methods achieve higher fitting accuracy. Table 3 provides an overview of various AI models that

are applied in production forecasting, highlighting their input parameters, prediction targets, and reservoir types. Production indices are primarily used to evaluate the current production status of oilfields and predict dynamic changes over time.

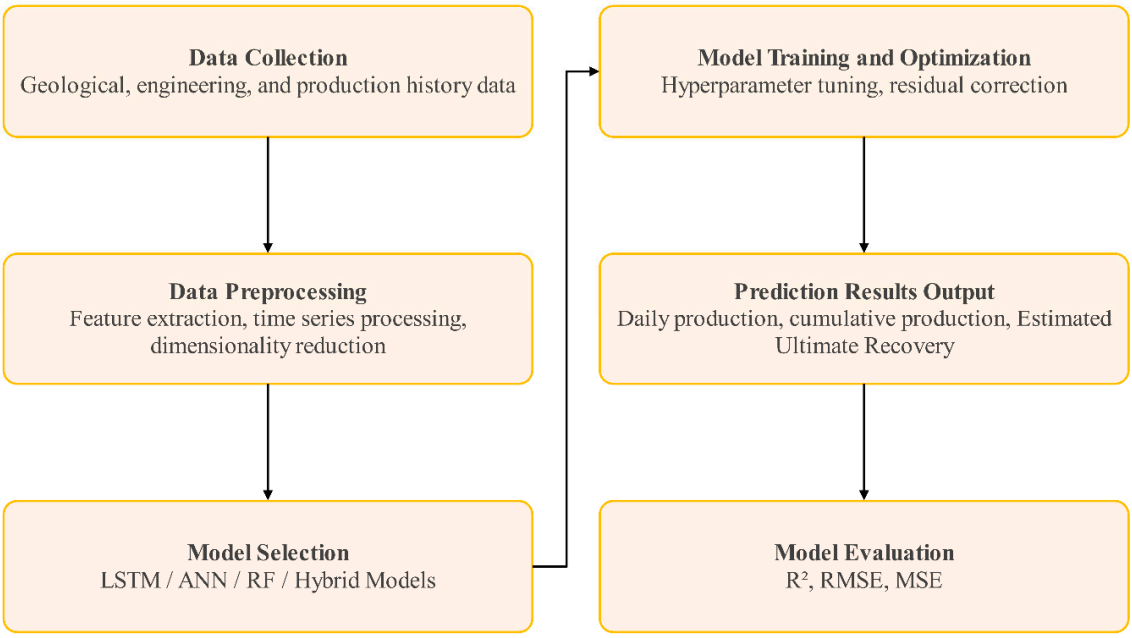


Figure 7. Workflow of Production Forecasting for Unconventional Oil and Gas Based on AI Models.

3.3.1. The LSTM Model

LSTM networks are highly effective at analyzing time-series data, making them a valuable tool for forecasting production trends in unconventional oil and gas fields. Alarifi and Miskimins (2021) have proposed an LSTM-SVR hybrid model, where LSTM captures the temporal dependencies in production data and Support Vector Regression (SVR) corrects the residuals of LSTM predictions [115]. This model outperformed traditional Decline Curve Analysis (DCA) methods in forecasting production decline and trends in unconventional reservoirs, highlighting the effectiveness of combining deep learning with traditional machine learning approaches to improve prediction accuracy.

Moreover, Qiu and Li (2022) applied Bayesian optimization to tune the hyperparameters of the LSTM model for daily production forecasting in tight gas reservoirs [116]. The optimized model achieved significant improvements in prediction accuracy and generalization capability, with a Mean Squared Error (MSE) markedly lower than other comparative models. This further validates the suitability of LSTM models for handling the complex production data of unconventional reservoirs.

3.3.2. The ANN/DNN Models

Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) have been widely applied in production forecasting for unconventional reservoirs due to their strong nonlinear fitting capabilities. Wang and Chen (2019) evaluated the applicability of DNN in production forecasting for the Bakken shale reservoir and used Sobol sensitivity analysis to identify the factors with the greatest impact on cumulative production [117]. Their results showed that the amount of proppant used per stage had the most significant influence on cumulative production.

Luo et al. (2022) proposed a DNN-based model to predict the Estimated Ultimate Recovery (EUR) of fractured horizontal wells in tight oil reservoirs [118]. Through hyperparameter optimization, the model significantly outperformed traditional linear regression models in

prediction accuracy. The study found that geological properties, such as matrix permeability, initial production rate, and porosity, had the greatest impact on EUR predictions.

However, ANN/DNN models face challenges in their application, such as requiring large volumes of high-quality data and a susceptibility towards overfitting. Therefore, further research is needed to develop effective feature selection methods, mitigate overfitting, and enhance model generalization capabilities.

3.3.3. The Random Forest Model

Random Forest (RF), an ensemble learning method, excels in handling high-dimensional and nonlinear data. Smith and Mukerji (2019) applied RF algorithms to predict production curves for unconventional resources using geological, geophysical, and engineering data, achieving prediction accuracies (R^2) ranging from 65% to 76% [119]. Bhattacharyya and Vyas (2022) used RF models for the rapid forecasting of production decline and EUR for Bakken shale oil wells, identifying initial flow rate, proppant volume, and fracturing fluid volume as key variables influencing production decline predictions [120].

While RF models perform well in forecasting, their "black box" nature can limit the interpretability of their prediction results. Therefore, integrating feature importance analysis to improve the model's interpretability remains a key focus for future research.

3.3.4. The Hybrid CNN–RNN Model

To simultaneously capture spatial and temporal features, researchers have combined Convolutional Neural Networks (CNN) with Recurrent Neural Networks (RNN). Zhou and Guo (2023) have proposed the CNN–BiGRU–AM model, which integrates CNN for spatial feature extraction, Bidirectional Gated Recurrent Units (BiGRU) for temporal feature processing, and an Attention Mechanism (AM) for weight adjustment, enabling an efficient production forecasting for shale oil [121]. This model outperformed traditional machine learning and deep learning methods in prediction accuracy.

Hybrid models effectively leverage the strengths of different networks but also increase model complexity. In practical applications, balancing model complexity with prediction accuracy and computational resource limitations is essential.

3.3.5. Other AI Models

In addition to the aforementioned models, other AI algorithms have also been applied to production forecasting for unconventional reservoirs. Kong and Chen (2021) employed a stacked model combining XGBoost and linear regression to predict cumulative oil and gas production, achieving an R^2 of 0.80 and demonstrating strong predictive performance [122].

The selection of different models depends on specific application scenarios, data characteristics, and forecasting requirements. Future research should focus on developing more generalizable models to adapt to the complex and dynamic production environments of unconventional reservoirs.

A summary of the different AI-based production forecasting models, their input parameters, and performance in unconventional reservoirs is provided in Table 3.

Table 3. Applications of AI in Unconventional Reservoir Production Forecasting.

Reference	Method	Input Parameters	Output Parameters	Resource
[119]	RF	Geological data, seismic attributes, engineering data	Principal Component scores of production curves	Eagle Ford shale oil
[121]	CNN, BiGRU, AM	Wellhead pressure, tubing pressure, output pressure, daily fluid balance volume	Daily shale oil production rate	Shale oil
[123]	ARIMA, LSTM, PRO	Monthly production history	Future production forecast	DJ Basin shale oil

Table 3. *Cont.*

Reference	Method	Input Parameters	Output Parameters	Resource
[124]	ANN, DNN, SVM, RF, XGBoost, LSTM	Geological, production, and engineering parameters	Production forecast curves	Shale oil/gas
[125]	RNN	Rock mechanical properties, completion variables, well spacing	Cumulative production over five years	Montney shale gas
[115]	ANN	Production history, completion parameters, decline curve analysis ultimate recovery	Estimated ultimate recovery	-
[117]	DNN	Well location, formation thickness, fracture parameters, proppant parameters	Cumulative production over six and eighteen months	Bakken shale oil
[120]	RF	Initial production rate, proppant amount, fracture fluid volume, completion length	Decline model parameters and estimated ultimate recovery	Bakken shale oil
[126]	ANN	Completion parameters, geological attributes	Cumulative production over the first six months	Shale oil
[118]	DNN	Geological attributes, completion parameters, production parameters	Estimated ultimate recovery	Tight oil
[127]	LSTM, SVR	Wellhead pressure, nozzle size, daily water production	Daily oil and gas production	Bakken shale oil
[128]	LSTM	Production data series	Future production forecast	Sichuan Basin shale gas
[116]	Opt-LSTM	Wellhead pressure, reservoir temperature, water production, gas production rate	Daily gas production	Ordos Basin tight gas
[129]	TL, LSTM	Completion parameters, formation properties, fluid properties, early production data	Long-term oil, gas, and water production curves	Bakken shale oil
[122]	XGBoost, LR	Geological, drilling, completion, production, and economic factors	Cumulative production over the first twelve months	Duvernay shale oil
[130]	MLP, CAE	Geological parameters, fracture parameters	Cumulative gas production and daily gas production rate	Shale gas

3.4. Applications of AI in Hydraulic Fracturing for Unconventional Oil and Gas

Due to the low porosity and low permeability characteristics of unconventional oil and gas reservoirs, hydraulic fracturing has become a key technology for enhancing the recovery of these resources. However, traditional methods for fracturing design and optimization often struggle to make optimal decisions when faced with complex geological conditions and numerous uncertain parameters. The introduction of artificial intelligence (AI) technologies offers new approaches for optimizing fracturing design, predicting fracture parameters, and enabling real-time control (as illustrated in Figure 8).

In recent years, significant progress has been made in fracture parameter prediction and fracturing optimization design through machine learning and deep learning algorithms. Models such as XGBoost, Deep Neural Networks (DNN), and Variational Autoencoders (VAE) have been used for high-precision predictions of fracture geometry parameters [131–133]. By accurately predicting key parameters during the fracturing process, such as fracture height, length, and conductivity, engineers can make real-time adjustments to the fracturing plan, thereby improving fracturing effectiveness and economic benefits.

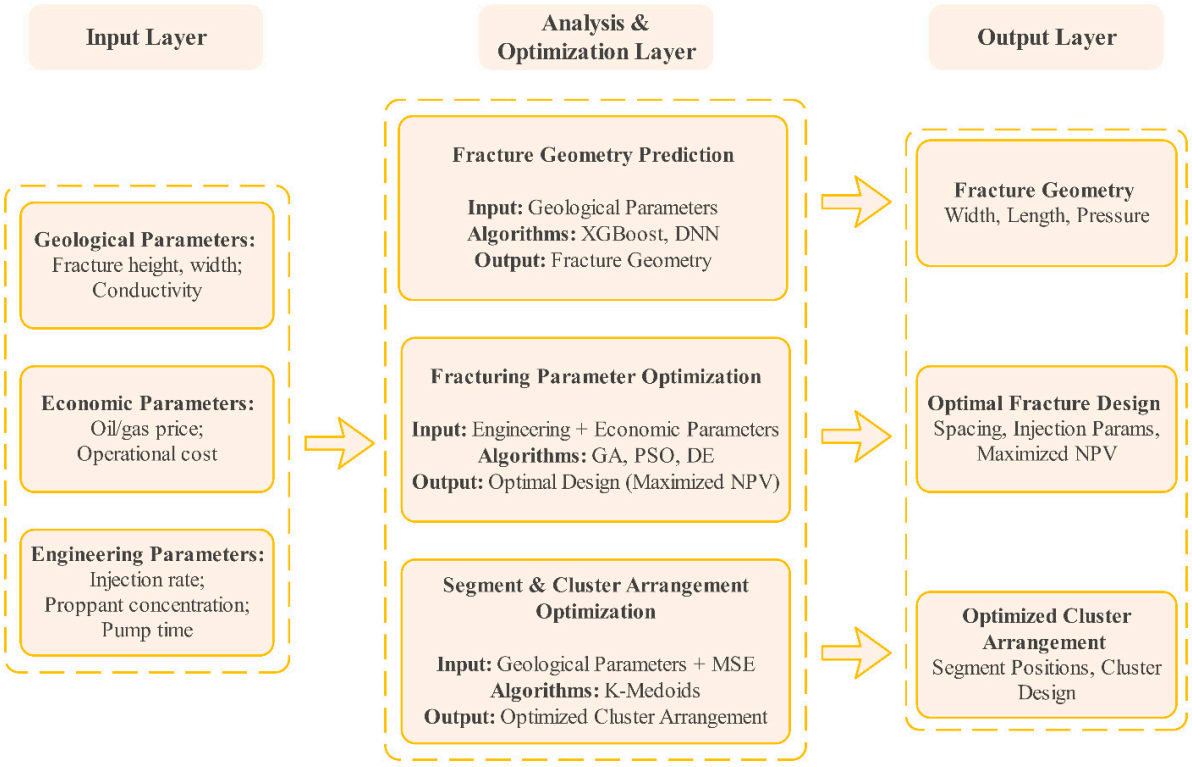


Figure 8. AI-Based Hydraulic Fracturing Optimization.

Optimization algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) are widely used for selecting the best fracturing parameters and well placement [134–136]. Some studies have combined PSO with Gaussian Process Regression (GPR) to develop a more efficient framework for optimizing regional hydraulic fracturing design and well placement, reducing computational costs and improving economic returns (Net Present Value, NPV).

Furthermore, methods that integrate machine learning models and numerical simulations have also been developed. Surrogate models, such as Multi-Layer Perceptron (MLP) and Deep Belief Networks (DBN), have been used to replace high-computational-cost numerical simulations, enabling rapid predictions of production performance and optimization of fracturing parameters [137–139]. Table 4 provides an overview of different AI models used in hydraulic fracturing optimization, along with their input parameters and prediction targets. This approach increases computational efficiency while maintaining high prediction accuracy, making it suitable for real-world engineering applications under complex geological conditions.

It is also worth noting that unsupervised learning algorithms have shown unique advantages in fracturing design optimization. By performing K-Medoids clustering analysis on bottom-hole mechanical specific energy (MSE) data, fracturing cluster arrangement in horizontal wells can be optimized to achieve a balanced fracturing effect across the reservoir [140]. This method does not require supervised data, making it applicable to reservoirs with significant layer strength variations. Table 4 provides a summary of various AI-based methods applied in hydraulic fracturing, including different models, input parameters, and prediction outcomes.

Table 4. Applications of AI in Hydraulic Fracturing for Unconventional Oil and Gas.

Reference	Method	Input Parameters	Output Parameters	Resource
[131]	XGBoost + BO	Fracture height, fracture length, injection rate	Fracture width, fracture pressure	Shale oil and gas
[141]	ANN + BP	Source-reservoir combination parameters	Shale oil production	Shale oil
[134]	GPR + GA	Horizontal well length, fracture half-length	Optimized fracturing parameters and well placement	Shale gas
[135]	GA, PSO, DE	Number of fracturing stages, fracture half-length	Optimal fracturing configuration	Shale gas
[138]	MLP + PSO	Fracture parameters, well location	Net Present Value (NPV), Cumulative Gas Production (CGP)	Shale gas
[140,142]	K-Medoids Clustering	Mechanical Specific Energy (MSE) data	Optimized fracture cluster arrangement	-
[132]	DNN + PSO	Fracturing parameters, sweet spot distribution	Cumulative production, NPV	Shale oil
[136]	MLP + DE	Fracture parameters	NPV	Shale gas
[139]	Improved NN	Fracturing parameters, physical features	NPV	Shale gas
[133]	VAE + RNN	Production data	Fracture distribution map	-

An analysis of existing research reveals that AI has made significant advances in fracturing design and fracture prediction, but some challenges remain. Firstly, models generally rely on historical data, and the high uncertainty of data during fracturing carries the potential for a high number of errors in practical applications. Second, although optimization algorithms excel in accelerating calculations and improving efficiency, how to further enhance their adaptability and accuracy under complex geological conditions remains a challenge. Therefore, future research should focus on improving the robustness of models when faced with incomplete and unstable data, especially in handling data variations under dynamic geological conditions. Additionally, integrating physical laws with intelligent algorithms and exploring new data fusion strategies will be crucial to further enhance the accuracy of real-time decision-making and optimization processes.

3.5. Applications of AI in EOR Methods for Unconventional Oil and Gas

Unconventional reservoirs are characterized by complex geological conditions and multiple flow regimes, presenting significant challenges for traditional Enhanced Oil Recovery (EOR) methods. AI provides new approaches to address these issues, particularly in the areas of parameter prediction and strategy optimization.

Chen et al. (2022) employed a Backpropagation (BP) neural network model to successfully predict the diffusion coefficient of CO_2 in crude oil, providing crucial insights for optimizing CO_2 flooding in tight and shale reservoirs [143]. Similarly, Qin and Li (2023) used a Genetic Algorithm-optimized BP neural network (GA-BP neural network) to precisely predict the CO_2 displacement efficiency in shale reservoirs, revealing the significant impact of injection pressure, soaking time, and porosity on displacement efficiency [144].

In the optimization of EOR strategies, AI combined with numerical simulation methods has demonstrated great potential. Wan and Jin (2022) integrated the Embedded Discrete Fracture Model (EDFM) with neural networks and Markov Chain Monte Carlo (MCMC) methods to optimize fracture characterization and CO_2 injection strategies in unconventional reservoirs, leading to enhanced recovery rates [145]. Zhao and colleagues (2024) employed a combination of deep neural networks and numerical simulations to achieve precise monitoring and production forecasting of the gas injection EOR process in the Bakken tight oil reservoir, providing a foundation for real-time optimization [146].

Furthermore, machine learning has made significant progress in predicting gas adsorption behavior in unconventional reservoirs. Tavakolian et al. (2024) applied various

algorithms, including Random Forest, Decision Trees, and Support Vector Machines, to successfully predict the adsorption capacity of CH_4 and CO_2 in tight reservoirs [147]. A detailed summary of different AI-based EOR models and their applications in unconventional oil and gas reservoirs is presented in Table 5. This provides theoretical guidance for enhancing coalbed methane and shale gas recovery (ECBM and ESGR). Table 5 provides a summary of various AI-based EOR applications, highlighting different models, input parameters, and prediction targets.

Table 5. Applications of AI in EOR for Unconventional Oil and Gas.

Reference	Method	Input Parameters	Output Parameters	Resource
[143]	BP	Temperature, pressure, oil density, oil viscosity, permeability, porosity, surface area, volume	CO_2 diffusion coefficient	Tight oil and shale oil
[145]	NN + MCMC	Fracture efficiency, fracture half-length, fracture height, fracture width, conductivity, water saturation, fracture compressibility, reservoir compressibility	Production history matching solution	-
[148]	DNN	Reservoir pressure, porosity, fracture permeability, fracture width, conductivity, permeability contrast	Recovery prediction	-
[147]	RF, DT, SVR, XGBoost, ANN	CO_2 ratio, rock type, total organic carbon, moisture content, temperature, pressure	CH_4 and CO_2 adsorption amount	Shale gas and coalbed methane gas
[146]	DNN + Numerical Simulation	Pressure, temperature, injection volume, composition, fracture permeability, injection rate	Production prediction, gas breakthrough time	Bakken tight oil
[144]	GA + BP	Porosity, total compressibility, oil saturation, total organic carbon, median pore size, permeability, soaking time, injection pressure	CO_2 displacement efficiency	Shale oil

AI has shown considerable advantages in the field of unconventional oil and gas EOR, but there remains room for improvement in several areas. Existing models often rely heavily on historical data, and their generalization ability could be further strengthened. Additionally, current research generally focuses on single physical processes, neglecting the impact of complex multi-field couplings. Future work should explore deep learning models that integrate multi-physical field couplings. Moreover, the integration of AI with traditional engineering methods is still not sufficiently close, and future research should focus on effectively combining AI with numerical simulations, physical experiments, and other methods to enhance the real-time capabilities and accuracy of oil and gas development.

3.6. Applications of AI in HSE Management for Unconventional Oil and Gas Projects

In the development of unconventional oil and gas resources, Health, Safety, and Environmental (HSE) management is a critical component to ensure the sustainable use of resources and the protection of the ecological environment. Traditional HSE risk assessment methods and environmental monitoring techniques often face challenges such as complex data, poor real-time capabilities, and difficulty handling multiple variables. In recent years, the rapid development of artificial intelligence (AI) technologies has provided new solutions for HSE management in unconventional oil and gas development.

AI algorithms, such as logistic regression and neural networks, have been successfully applied in HSE-related fields, including groundwater methane contamination detection, shale gas industry risk prioritization, and reservoir fluid leakage monitoring. Wen et al. (2021) constructed a logistic regression model to identify abnormal methane concentrations in groundwater in various oil and gas production areas in the United States. This model effectively monitors the impact of unconventional oil and gas extraction on water quality, ensuring environmental safety [149]. By analyzing multiple water chemical parameters, this method enables rapid identification of a potential contamination, improving the efficiency and accuracy of environmental monitoring.

In the area of health and safety risk assessment, BP neural networks have been used to quantify and prioritize multidimensional risks in China's unconventional shale gas

industry [150] (the risk assessment workflow is illustrated in Figure 9). The model considers a range of risk factors, including resource availability, economics, technology, environment, and social policies, helping decision-makers prioritize HSE risk management. This AI-based assessment method overcomes the limitations of traditional methods that struggle with handling complex nonlinear relationships, enhancing the scientific and objective nature of risk assessments.

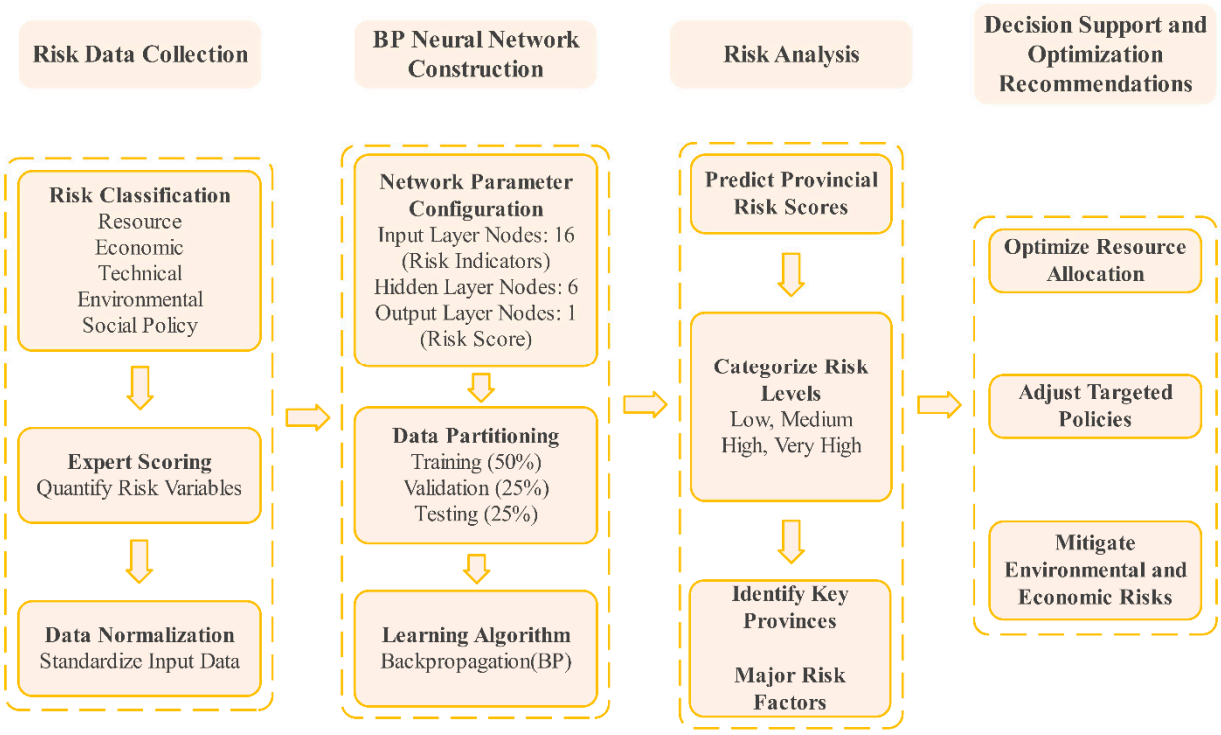


Figure 9. Risk Assessment Workflow Based on BP Neural Network.

Beyond HSE management, AI is now playing an increasingly critical role in real-time field monitoring, intelligent reservoir management, and predictive analytics for unconventional oil and gas development. Many global oil and gas companies have actively adopted AI-based solutions to optimize operations and maximize production efficiency. In the next section, we summarize the industrial applications of AI in unconventional oil and gas development, focusing on practical case studies and their implementation in the industry.

In addition, for geological CO_2 sequestration projects, a leakage detection method using a multivariate linear regression model has been applied. This method relies only on injection rate and bottom-hole pressure data to enable real-time monitoring of fluid leakage in reservoirs [151]. By not relying on complex geological models, this approach reduces monitoring costs and improves early detection capabilities for leakage events, helping prevent environmental and safety risks.

In summary, AI technologies have demonstrated significant advantages and potential in HSE management for unconventional oil and gas development. However, current applications are mostly focused on specific aspects, and a comprehensive and systematic solution has not yet been developed. Future research should focus on constructing an integrated AI-based HSE management platform, combining Big Data analytics and advanced machine learning algorithms to enable real-time monitoring and risk warnings throughout the entire unconventional oil and gas development process. This will help improve the safety of resource development, reduce environmental risks, and promote the sustainable development of the unconventional oil and gas industry.

3.7. Industrial Applications of AI in Unconventional Oil and Gas

The application of artificial intelligence (AI) in unconventional oil and gas fields, including shale gas, tight oil, and heavy oil, has gradually evolved into a diversified landscape. AI technologies are now integrated across the entire workflow, spanning exploration, logging, drilling, hydraulic fracturing, production management, and surface facility operations. Major oil and gas companies such as Shell, Chevron, BP (British Petroleum), Total, and ExxonMobil have implemented intelligent oilfield initiatives, leveraging real-time monitoring, Big Data analytics, and deep learning models to optimize well placement, production strategies, and injection-production management [11]. For instance, Total has collaborated with Google Cloud to develop automated seismic data processing techniques and enhance decision support systems based on large-scale downhole sensor data [152]. In North American shale gas fields, Halliburton and Noble Energy have achieved a high level of technological maturity in drilling optimization and real-time monitoring.

For pipeline and surface facility management, companies such as Shell, Chevron, and ExxonMobil have deployed machine learning models for predictive maintenance, transportation scheduling, and corrosion detection [153]. Additionally, BP (British Petroleum), Shell, Total, and Saudi Aramco have adopted digital oilfield technologies such as intelligent water flooding, fiber optic sensing, and automated seismic interpretation to maximize the potential of unconventional reservoirs [154].

To address challenges such as missing logging data and complex well conditions in unconventional reservoirs, Shell and Quantico Energy Solutions have employed neural network algorithms to synthesize missing well logs, improving formation evaluation accuracy [155]. In collaboration with the C3 IOT platform, Shell has integrated predictive maintenance and well management solutions into a unified data analytics framework, optimizing artificial lift systems and supply chain logistics [156]. In North America's unconventional fields, ExxonMobil has deployed a closed-loop AI-based gas lift optimization system in the Permian Basin, enabling real-time gas injection adjustments and enhancing individual well productivity. Similarly, Vital Energy has leveraged real-time data acquisition and machine learning inference for electrical submersible pumps (ESP), significantly improving well output and extending pump lifespans [157].

Case studies from the Southwest South China Sea oilfield, Dagang oilfield, Fuling shale gas field, and Kuwait's heavy oil block illustrate the effectiveness of AI algorithms such as neural networks and particle swarm optimization in well testing design, injection-production optimization, and thermal recovery management. By optimizing water or steam injection strategies, these applications have enhanced recovery efficiency while significantly reducing operational costs. In the Fuling shale gas field, real-time monitoring and dynamic parameter adjustments have improved hydraulic fracturing efficiency and single-well productivity. In Kuwait's heavy oil block, data-driven intelligent reservoir management has contributed to increased production rates and reduced operating expenses [158].

The industrial-scale adoption of AI in unconventional oil and gas development continues to expand, covering logging, drilling, fracturing, artificial lift, production optimization, and pipeline integrity management. Across North American shale plays, Chinese shale gas fields, and international heavy oil resources, enterprises have achieved enhanced efficiency and cost reduction through multi-source data integration, automated control, and predictive maintenance, demonstrating the broad applicability of AI. Future advancements should focus on interdisciplinary data fusion, model interpretability, and fully automated decision-making to further drive the efficient, safe, and sustainable utilization of unconventional oil and gas resources.

4. Limitations

(1) Data Quality and Availability Constraints

The development of unconventional oil and gas fields heavily depends on high-fidelity geological and engineering data. However, data collection is often limited by cost, equipment accuracy, and field conditions. On one hand, logging and seismic data, which are required for geological evaluation, often suffer from missing curves and insufficient resolution. On the other hand, the lack of standardized formats, parameter identifiers, and processing norms across different regions and reservoirs leads to mismatches or biases in data integration and feature extraction. Additionally, measurement errors and noise are inevitable, reducing the stability and generalization capabilities of AI models.

(2) Limited Generalization Capability of Models

Unconventional reservoirs exhibit significant regional differences in geological conditions and fluid behavior, resulting in the poor adaptability of models in geological environments not covered by the training data. Deep learning models are prone to overfitting when trained on small datasets, performing well during training but showing a marked decline in accuracy when predicting new well locations or different basins. The lack of effective strategies for model transfer and adaptation poses a challenge for the practical deployment and scalability of AI models.

(3) Poor Model Interpretability and Lack of Physical Significance

Current deep learning and complex black-box models prioritize prediction accuracy but often fail to provide clear and transparent decision-making paths. The absence of embedded constraints based on geological and engineering mechanisms sometimes leads to results that contradict fundamental principles of fluid flow, lithological characteristics, or mechanical behavior. This lack of physical interpretability reduces confidence in model predictions, limiting their acceptance and adoption by engineers and geologists.

(4) Insufficient Integration of Domain Knowledge and Physical Constraints

Most existing models are data-driven and fail to incorporate complex reservoir characteristics, rock mechanics, and fundamental physical laws underlying engineering practices. This purely data-driven modeling approach has limitations in the highly heterogeneous and dynamic conditions of unconventional oil and gas environments. The absence of domain knowledge and physical constraints increases the likelihood of producing physically unrealistic results, reducing the practical value of models for decision-making and optimization.

(5) Conflict Between Computational Costs and Real-Time Requirements

Deep learning and complex optimization methods require extensive computational resources for processing large-scale, high-dimensional data and parameter optimization. These methods demand high-performance computational facilities and incur substantial time costs during training and inference. Unconventional oil and gas exploration and development often require real-time or near-real-time responses, but excessive computational demands can lead to decision delays, hindering timely operational adjustments and safety assurance.

(6) Practical Barriers to Technology Integration and Application

Embedding AI models into existing development workflows faces challenges such as data interface incompatibility, system integration issues, and software interoperability. There is a lack of universal tools and platforms tailored to unconventional oil and gas scenarios, as well as standardized products and unified interfaces that meet industrial application requirements. These factors hinder the widespread adoption and mature deployment of AI technologies, leaving many research outcomes difficult to translate into effective field applications.

5. Prospects

(1) Establishing High-Quality Data Sharing and Standardization Systems

Unconventional oil and gas development urgently requires the establishment of unified data standards and identifiers to ensure compatibility and integration of geological and engineering data across different production regions. A robust industry-wide data-sharing platform should be developed to integrate resources from multiple sources, expanding the range of training datasets for AI models and creating a stronger foundation for model generalization and adaptation to diverse geological conditions.

(2) Integrating Domain Knowledge and Physical Constraints to Develop Physics-Driven AI Models

Purely data-driven predictions are prone to violating physical laws. Therefore, fundamental principles, such as geomechanics and fluid dynamics, should be incorporated into AI model construction to ensure alignment with the mechanical characteristics of reservoirs, fluids, and wellbores. By integrating physical models with data-driven models, hybrid approaches can be developed that offer both accuracy and interpretability, addressing the dual demands for rationality and reliability in practical applications.

(3) Enhancing Model Generalization and Adaptability

Given the variability of geological conditions in unconventional reservoirs, AI models must demonstrate stronger adaptability across regions. Transfer learning can enable models trained in specific regions to quickly adapt to new conditions, reducing dependence on large-scale datasets. Additionally, exploring privacy-preserving collaborative training methods, such as federated learning, can enhance model generalization without compromising data security.

(4) Improving Model Interpretability and Transparency

Explainable AI techniques should be employed to visually present model decision mechanisms and feature importance, enabling R&D and field teams to quickly understand the logic behind the model's responses to input parameters. Techniques such as rule extraction and pattern recognition can transform the internal reasoning of complex deep learning models into clear, actionable decision-making guidance for engineering practices.

(5) Optimizing Computational Resources and Model Efficiency

The high computational costs of AI models conflict with the real-time decision-making demands of unconventional oil and gas operations. Techniques such as model compression, parameter quantization, and the integration of high-performance computing resources can effectively reduce resource consumption during training and inference. This optimization will support rapid iteration and real-time field applications.

(6) Building Integrated Intelligent Management Systems for Oil and Gas Fields

The future development of unconventional oil and gas fields should integrate AI with technologies such as the Internet of Things, cloud computing, and Big Data analytics to construct intelligent production management platforms. Through real-time data acquisition, dynamic optimization, and automated control, such systems can achieve the comprehensive regulation of wellbores, reservoirs, and surface facilities, significantly improving decision-making efficiency, safety, and economic performance in resource development.

6. Conclusions

In conclusion, artificial intelligence (AI) technologies in unconventional oil and gas development have evolved from isolated trials to full-process applications, currently transitioning from traditional data processing methods to the integration of geological and

engineering mechanisms. The combined use of deep learning, machine learning, and intelligent optimization algorithms has continuously enhanced the ability to predict and analyze key parameters such as gas-bearing probability, lithological characteristics, brittleness index, and production variations. These improvements provide solid support for efficient exploration, production optimization, and environmental risk management in unconventional oil and gas fields. AI has continuously evolved to adapt to different geological conditions. Advances in theory and technology are reshaping development models and improving decision-making. Moving forward, in a global context characterized by varied resource quality, complex and changing geological environments, and dual constraints of economic and environmental factors, further theoretical research into the geological characteristics and flow behavior of unconventional reservoirs, along with a deeper integration of data, models, and mechanisms, will be essential. This will not only be a key pathway for maintaining technological leadership and controlling development costs but also a foundation for achieving high-quality, sustainable development. As physical constraints, cross-regional transfer learning, and efficient computational systems continue to improve, AI is poised to play a more significant and long-term role in enhancing the efficiency and quality of unconventional oil and gas development, providing strong technological support for the industry's ongoing progress and long-term competitiveness. Additionally, AI has already demonstrated its industrial impact, with major oil and gas companies leveraging AI for intelligent field management, production forecasting, and operational efficiency enhancement. The successful deployment of AI-driven solutions in unconventional oil and gas fields highlights its transformative potential for the industry. Future efforts should focus on refining AI methodologies to further integrate them into industrial workflows, ensuring continuous improvements in efficiency and sustainability.

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Abbreviations

The following abbreviations are used in this manuscript:

CNN	Convolutional Neural Network
ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
RBF	Radial Basis Function
FCDN	Fully Connected Deep Network
DNN	Deep Neural Network
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
Bi-LSTM	Bidirectional Long Short-Term Memory
BiGRU	Bidirectional Gated Recurrent Unit
SVM	Support Vector Machine
SVR	Support Vector Regression
RF	Random Forest
XGBoost	Extreme Gradient Boosting
GB	Gradient Boosting
VAE	Variational Autoencoder
TL	Transfer Learning
ARIMA	AutoRegressive Integrated Moving Average
PRO	Prophet
AM	Attention Mechanism
CAE	Convolutional Autoencoder
LR	Linear Regression
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimizer
ACO	Ant Colony Optimization
MPSO	Mutation Particle Swarm Optimization
MCMC	Markov Chain Monte Carlo
DE	Differential Evolution
STNet	Spatiotemporal Network
SSGCN	Spatial-Sequential Graph Convolution Network
FL	Fuzzy Logic
ANFIS	Adaptive Neuro-Fuzzy Inference System
BP	Backpropagation
ELM	Extreme Learning Machine
DCT	Discrete Cosine Transform
Improved NN	Improved Neural Network
EUR	Estimated Ultimate Recovery
NPV	Net Present Value
HSE	Health, Safety, and Environment
BI	Brittleness Index
Input Parameters in the table	
Seismic Attributes	Amplitude, frequency, phase, dip, curvature, and similarity.
Well Logging Data	Gamma ray (GR), resistivity (RT), density, acoustic impedance (AI), velocity (Vp, Vs), porosity, Poisson's ratio, and more.
Reservoir Properties	Porosity, permeability, saturation, thickness, fracture properties, compliance coefficients, and total organic carbon (TOC).

Fracture Parameters	Fracture height, length, width, pressure, efficiency, conductivity, and compressibility.
Fluid Properties	Oil viscosity, oil density, gas composition, water saturation, and CO_2 diffusion coefficient.
Production Data	Production rates (oil, gas, water), cumulative production, production time, and initial production rates.
Operational Conditions	Pressure, temperature, injection volume, injection rate, and soaking time.
Geological Data	Brittleness index, TOC, and water saturation.
Elastic Attribute Data	Young's modulus, Poisson's ratio, P-wave and S-wave velocities.
Completion Parameters	Proppant amount, fracture fluid volume, and completion length.
NMR Features	Porosity, T2 relaxation time, and pore size distribution.
Mechanical Specific Energy (MSE)	Work required to break the rock during drilling.
Rock Image Features	Features extracted from digital rock images (e.g., using DCT).
Sweet Spot Distribution	Areas with high production potential.
Source-Reservoir Combination Parameters	Geological and reservoir characteristics.
Production and Operational Data	Production rates, injection volumes, market prices, and water depth.
Output Parameters in the table	
Production Metrics	Daily production, cumulative production, recovery prediction, gas breakthrough time, and estimated ultimate recovery (EUR).
Fracture Metrics	Fracture index, optimized fracture parameters, and fracture distribution maps.
Reservoir Properties	Porosity, permeability, saturation, lithofacies, and mineral composition (e.g., quartz, clay).
Economic Metrics	Net Present Value (NPV) and production error (e.g., RMSE).
Geological Metrics	Brittleness index, TOC, and sweet spot distribution.
Phase and Component Metrics	Phase state, component concentrations, and CO_2 diffusion coefficients.
Adsorption Capacity	CH_4 and CO_2 adsorption under specific conditions.
Forecasting Metrics	Production curves, future production forecasts, and principal component scores.
Efficiency Metrics	CO_2 displacement efficiency and oil recovery efficiency.
Gas Probability Distribution	Probability map of gas presence.

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