

Research Progress on the Application of Machine Learning in Oil and Gas Exploration and Development

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Abstract. Machine learning becomes a powerful tool for large-scale data processing and analysis in the oil and gas industry with its automation, intelligence, efficiency and high accuracy. This paper summarized the current status of the application of machine learning in oil and gas exploration and oil and gas field development in recent years. This paper discussed the current problems faced by the application of machine learning in oil and gas exploration and development. Besides it looked forward to the future. It was found that machine learning helped to improve the efficiency and accuracy of exploration and production and reduce the risk of exploration. Apart from that, machine learning also changed the operation mode of E&P to a certain extent.

Keywords: Machine Learning, Oil and Gas Exploration, Oil and Gas Field Development, Future Prospects.

1. Introduction

Since the 1960s, Chinese petroleum industry had developed vigorously. But at present, the main old oilfields, such as Daqing Oilfield, Changqing Oilfield and Shengli Oilfield, have generally entered into the late development stage of high or very high water content. It was difficult to utilize the remaining recoverable reserves efficiently and crude oil production was reduced [1]. At the same time, oil and gas in the process of exploration and development not only produced a large amount of data but also faced the complexity and uncertainty of even other challenges. Improving the accuracy and efficiency of data analysis, optimizing the use of resources, and increasing the recovery rate of oil and gas became urgent problems in the oil and gas industry. The ultimate goal was to reduce the cost of oil and gas production. In this context, machine learning with its powerful data analysis capabilities, was widely used in all aspects of the oil and gas industry.

In recent years, the global oil and gas industry has been actively promoting digital transformation. This has led to significant breakthroughs and advancements in machine learning, opening up new possibilities for the exploration and development of oil and gas resources. This paper summarized the application of machine learning in oil and gas exploration and oil and gas field development in recent years. However, there were also challenges facing the application of machine learning in the oil and gas industry. These included limited depth of application, difficulties in acquiring and sharing data on time, and a shortage of professionals with composite skills. Nonetheless, the future outlook for machine learning in the oil and gas industry remained promising.

2. Machine Learning Overview

Machine Learning was a technique in the field of Artificial Intelligence and the core of AI[2], whose goal was to enable computer systems to improve their performance through learning and pattern recognition. It utilized large amounts of data to train algorithms from which computers could learn and make predictions or decisions. Machine learning includes methods such as supervised

learning, unsupervised learning, semi-supervised learning, and reinforcement learning. These methods were widely used in various fields such as image and speech recognition, natural language processing, recommender systems, financial forecasting, medical diagnosis, and so on. The development of machine learning has made great achievements and has constantly pushing the development of artificial intelligence technology. Nowadays, machine learning is widely used in the field of oil and gas exploration and development. It became one of the cutting-edge technologies in the industry and played an important role in the construction of intelligent oil fields.

3. Machine Learning in the Oil and Gas Industry

3.1. Application of machine learning in oil and gas exploration

Oil and gas exploration was a process that involved identifying potential areas for exploration and utilizing techniques like geological exploration and geophysical logging to search for and confirm the presence of underground oil and gas resources. Exploration served as the front end of the petroleum industry, playing a critical role in maintaining the stability of proven reserves and ensuring sustainable development within the industry. It also helped to meet national energy demands and improved the competitiveness of a country. Certainly, oil and gas exploration was a complex, high-risk, and high-uncertainty process. It involved extensive data analysis and interpretation, as well as intricate temporal and spatial relationships, requiring significant manpower and time investments. Therefore, machine learning in oil and gas exploration has gradually been applied and in recent years it has made a lot of new progress.

In terms of logging processing, in 2018, Zhang et al. [3] proposed a method of generating logging curves by string-level long short-term memory neural network (CLSTM) based on partially known curves. In 2019, Pham N et al. [4] utilized partially logged data and predicted to fill in missing logging data by using a bidirectional convolutional long short-term memory network (convLSTM). In 2020, Yang et al. [5] proposed an efficient machine learning modeling paradigm to solve the problem of complicated logging curves generation for multiple sources based on partially known curves. In 2021, In 2021, BITTAR M et al. [6] applied deep learning to depth matching of log curves and proposed a method of depth matching based on DQN. Based on the sequence information in logging data, Zhou et al. [7] applied the bidirectional gated cycle unit (BGRU) neural network to the reconstruction of acoustic logging curves, providing new possibilities for the prediction of acoustic logging curves. In the same year, Cacers et al. [8] established a one-dimensional convolutional neural network model using the measured values of each logging curve to realize the automatic depth matching of logging curves. In the following year, Teng et al.[9] proposed the use of a gated recurrent unit neural network (GRU) to predict the logging curves of undrilled formation. In general, the current logging curve prediction methods rely on the accuracy and completeness of the data. Therefore, in terms of logging processing, it is necessary to pay attention to the collection and processing of data.

In terms of data interpretation, in 2019, Wu X et al. [10] used a large number of seismic images to train a codec-based convolutional neural network model for automated fault identification and slope estimation. In the same year, PHAN S et al. [11] combined convolutional neural network and cascade method to build a learning model based on a deep Boltzmann machine for seismic inversion. Ma Y et al. [12] used a two-dimensional pixel convolution network to automatically acquire seismic data, and complete the first-to-wave pickup. In 2021, Min Qin et al. [13] integrated decision tree, support vector machine, random forest and extreme gradient boosting algorithms. They proposed the Stacking model fusion algorithm and built a model to identify high-temperature and high-pressure reservoir fluids. In the same year, Yan Chen et al. [14] combined support vector machine (SVM), gradient boosting decision tree (GBDT), and self-encoder based on each log curve to carry out the compartment identification. In 2022, Zhang Y et al. [15] proposed to suppress the noise based on improved ring generation adversarial network to improve the signal-to-noise ratio in response to the problem of more noisy data in shallow stratigraphic profiles. In 2023, Chen Juan et al. [16] proposed a crack detection method based on pixel-differential convolutional neural network, which effectively

improves the accuracy of crack identification, considering the insufficient information of the extracted local gradient.

In terms of model building and image recognition and classification, in 2017, Cheng et al. [17] used the RGB color space data of the original images of rock flakes. Then they employed convolutional neural networks and built pattern classifiers to achieve automatic recognition of granularity images. In 2021, Cheng et al. [18] proposed the method of using SqueezeNet-based convolutional neural networks to classify the images of rock flakes, which improved the speed and portability of the rock flake image classification algorithm speed and portability. In the same year, Li Liang et al. [19] proposed Tesseract-OCR technology based on recurrent neural network algorithm, which realized automatic and fast recognition of image data and converted them into text. In 2022, Wu Fan et al. [20] utilized various geological reservoir data to apply algorithms including gated recurrent unit (GRU) and multilayer perceptron. They aimed to establish a reservoir production capacity prediction model, ultimately solving the issue of processing offshore multi-source logging data. In the same year, under the premise of constructing a reservoir logging knowledge map, Liu et al. [21] combined several algorithms, including convolutional neural network and long and short-term memory neural network, to establish a knowledge-driven neural network reservoir identification and evaluation model. Their approach effectively addressed the small sample problem encountered in reservoir logging identification.

In terms of lithology identification and classification, in 2015, Mou et al. [22] integrated volcanic rock cores, rock mineral identification data and logging data to establish a volcanic rock core identification method based on support vector machine logging data. In the same year, Li et al. [23] used Restricted Boltzmann Machine (RBM) deep learning in logging lithology identification to extract logging lithology features and complete the automatic identification of lithology. In 2018, An Peng et al. [24] combined ReLu excitation function, Adagrad optimization algorithm, Softmax regression layer, etc. to construct a deep neural network model for lithology identification. In the same year, Kai Jiang et al. [25] established a lithology identification model based on Boosting Tree algorithm based on logging and logging data. In 2019, Yaxing Feng et al. [26] employed fresh surface images of rocks and twinned convolutional neural networks to extract both global and local rock features. They introduced an automatic lithology identification method based on the AlexNet twinned convolutional neural network. In 2020, Zhongyuan Wu et al. [27] utilized long and short-term memory neural network to extract and learn lithology depositional sequence features, which improved the lithology identification efficiency. In 2023, Chi Zhang et al. [28] developed a lithology identification method that integrated the longitudinal information of the reservoir. They constructed a model by combining logistic regression, support vector machine, random forest, convolutional neural network, and Stacking integrated learning. Their approach significantly enhanced the accuracy of lithology identification in logging. In the same year, Hou Mingyu et al. [29] established a graph-embedded neural network model based on knowledge graph to realize the intelligent identification of lithology. In general, the stability and mobility of the intelligent lithology identification method need to be improved. The generalization performance and reliability of the intelligent lithology identification method are the prerequisites for wide application.

In terms of reservoir prediction and evaluation, in 2015, Ding Jicai et al. [30] applied support vector machine to quantitative prediction of reservoir physical properties based on post-stack data. In 2017, Ni Weijun et al. [31] introduced a support vector machine-based method for predicting the transverse velocity of shale reservoirs. Their approach utilized conventional logging data and used support vector machines to establish correlations between the shale transverse velocity and each logging data. In the same year, Zhu Linqi et al. [32] integrated a deep confidence network fused with a nuclear limit learning machine and used NMR logging information for reservoir permeability prediction. In 2018, Lin Niantian et al. [33] identified and extracted seismic oil and gas characteristics by using known oil-gas well segment information based on convolutional neural network. Their approach aimed to achieve prediction of reservoir and oil and gas reservoir distribution. In the same year, Yu H Y et al. [34] utilized Gaussian processing regression algorithms to predict the TOC of

tight shale gas reservoirs. Tang et al. [35] established a model for calculating shale evaluation parameters using elemental logging data. They optimized and established a parameter calculation model based on multiple adaptive regression splines, neural network algorithms, and support vector machines. The results showed that the support vector machine algorithm had the best effect. In 2022, Zhang et al. [36] used the conventional logging curves of 7 wells in the Chepaizi area and the porosity determination of 62 Cretaceous sandstone samples. They also utilized production data of sampling wells and combined these with the Xgboost ensemble learning algorithm. The result was the establishment of a logging porosity prediction model that effectively predicted reservoir porosity in non-coring profiles.

In terms of phase identification and classification, in 2019, Xiao Ai et al. [37] quantitatively described logging curves and performed sample selection. They applied the support vector machine (SVM) classification algorithm to sedimentary phase identification, thereby achieving automatic classification and identification of sedimentary phases. In 2020, Xiao He et al. [38] selected 10 representative wells in the Yuanba area of northeastern Sichuan Province. They used conventional logging data and electrical imaging logging to describe their response characteristics to sedimentary microfacies. Finally, they used the systematic clustering method and Fisher discriminant method to construct an identification model to realize the automatic classification and identification of sedimentary microfacies. In the same year, Liu X Y et al. [39] combined low-dimensional global features and high-dimensional local features to propose a support vector machine lithofacies recognition method based on local deep multi-kernel learning. In 2023, Chen et al. [40] applied ensemble learning to petrographic logging recognition. They used the Bagging algorithm to combine the results of multiple base classifiers to realize automatic petrophase classification and recognition based on conventional logging curves. In the same year, Liu Zongbao et al. [41] applied the logging curve images to the petrographic phase identification model of dense sandstone reservoirs based on a convolutional neural network. They realized automatic classification and identification of petrographic phases using point-by-point scanning method.

Machine learning has been applied in the oil and gas exploration field, which improved efficiency, accuracy and reduced risk. Additionally, it had also altered the operation mode of exploration to some degree. By summarizing the application of machine learning in oil and gas exploration, the algorithms were convolutional neural network, generative adversarial network, etc., as shown in Table 1.

Table 1. Applications of machine learning algorithms in oil and gas exploration

Algorithm	Application
convolutional neural network	Fracture detection, fault identification, first-arrival wave pickup, image recognition, lithology identification, seismic noise suppression, reservoir prediction, Sedimentary phase (seismic, logging) identification
recurrent neural network	Log curve reconstruction, lithology identification, reservoir prediction, reservoir physical parameter prediction, seismic phase identification
BP algorithm	Fault recognition, image recognition, reservoir prediction, reservoir physical parameters prediction and optimization
support vector machine	Lithology identification, first-to-wave pickup, fracture identification and classification, reservoir fluid property identification, reservoir physical property parameter prediction, reservoir prediction and classification evaluation, sedimentary phase identification and classification
linear regression (math.)	Compartmentalized interlayer identification, fracture classification and evaluation, reservoir physical parameter prediction, and porous media performance prediction,
decision tree	Lithology identification, reservoir fluid property identification, petrographic classification, log phase analysis, reservoir prediction and classification evaluation, reservoir physical property parameter prediction
Maximum Expectation Algorithm	Seismic noise suppression, lithologic classification, reservoir prediction and classification, prediction of reservoir physical parameters
self-organizing map (math.)	Quantitative interpretation of seismic data, reservoir prediction, prediction of reservoir physical parameters
random forest	Synthetic logging curves, first-arrival wave pickup, lithology identification, petrographic classification, reservoir classification evaluation, reservoir physical property parameter prediction
clustering algorithm	Log curve reconstruction, lithology classification, reservoir classification evaluation, hydrocarbon reservoir prediction
Bayesian network	Fracture identification and classification, reservoir fluid property identification, reservoir classification and evaluation, geological risk evaluation
Generating Adversarial Networks	Geological imaging, fracture identification and classification, seismic phase identification

3.2. Application of machine learning in oil and gas field development

3.2.1. Application to yield forecasting

Production prediction was an important part of reservoir dynamic analysis, which not only related to the economic benefits of enterprises but also affected the market supply [42]. Compared with the traditional production prediction methods, using machine learning had a natural advantage. There was no need for formula derivation and geological modeling. Besides, the data came directly from the actual production data, which effectively avoided the interference of human factors and improved the efficiency of capacity prediction [43]. In addition, machine learning had stronger mapping ability and could more accurately reflect the nonlinear response relationship between oilfield production data.

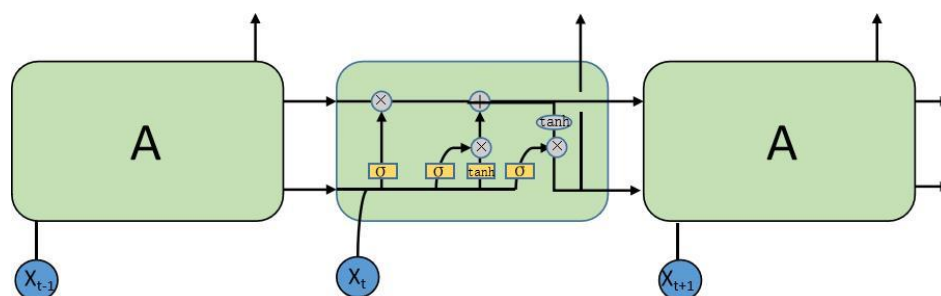


Figure 1. LSTM algorithm

Gu Jianwei et al [44] proposed a long and short-term memory network prediction model (as shown in Figure 1), which selected eight dynamic indicators as input layer input variables. That could realize the prediction of monthly oil production of any production well within the reservoir. Tian Zhixin established a BP-LSTM model. He used 14 static parameters of geological engineering to make a nonlinear prediction of the dynamic monthly production data of the new well. Liu Wei et al.[45] utilized the mean impurity reduction (MDI) method to screen 14 characteristic parameters. They then trained and optimized the LSTM model using daily oil production data. Xue Liang et al. [46] established a production dynamic prediction model based on long short-term memory deep neural networks. They used the particle swarm optimization algorithm to optimize the hyperparameters of the neural network model, which improved the prediction effect of long short-term memory deep neural networks. Xue Yongchao et al.[47] established a deep forest production prediction model and optimized the model parameters using grid-based search. The deep forest algorithm had high computational efficiency and more accurate prediction results compared with traditional machine learning algorithms such as BP neural network and random forest. Han Yidong et al.[48] gave an embedded extraction method combining two machine learning methods, Random Forest and XGBoost. The researchers used the two methods to rank the importance of feature parameters that impact production capacity. They further optimized the combination of the BP neural network and support vector machine to enhance the accuracy and stability of the prediction results. In general, machine learning has achieved good application in production forecasting. Various scholars have proposed their own models based on the obtained production data. But data-driven approaches are unexplainable and don't provide follow-up guidance.

3.2.2. Application to automated history fitting

Reservoir numerical simulation history fitting involved iteratively adjusting reservoir model parameters to match the historical production data. The aim was to ensure that the simulation results computed based on the adjusted reservoir model closely resembled or matched the measured values of historical production data. [49]. Due to the large uncertainty of the reservoir model itself and the multi-solution nature of the inverse problem, the future production prediction based on the model was inaccurate or even wrong. In addition, manual history fitting relied on the fitting experience of the workers. It adopted the "trial-and-error method" to gradually achieve the fitting effect, which was a time-consuming and laborious fitting process. On the other hand, machine learning had strong nonlinear dynamic processing ability, especially suitable for large-scale, complex structure, and unclear information system. These characteristics were common in reservoir research [50]. Zhang Liming et al [51] constructed an automatic history fitting method for reservoirs based on ensemble data assimilation and automatic searching of neural network architectures. The results showed that the automatic history fitting method, which automatically searched for the optimal neural network architectures after optimization, could more accurately extract the geologic features of the numerical model of reservoirs. Lu Yi et al. [52] employed the automatic history fitting method based on the SPSA algorithm to obtain multiple history fitting models that conformed to reservoir dynamics but contained different features. The results demonstrated that these multiple models could better approximate the real situation in the subsurface. Lee et al. [53] proposed the automatic history fitting method based on a particle swarm algorithm. They found that the particle swarm algorithm converged effectively under the updating of the control parameters. The history fitting method improved the accuracy of the full-field model. Santoso et al [54] proposed automatic history fitting with Bayesian Markov chain Monte Carlo (MCMC). Vo Thanh et al [55] utilized an artificial neural network for history fitting.

3.2.3. Joint data-physical drive

Machine learning was applied in various fields of oilfield development. However, most of the existing methods were based on purely data-driven machine-learning models. It suffered from high data demand, unstable prediction ability, and weak generalization ability. The models could not

consider the physical laws embedded in the data. The Traditional machine learning model is shown in Figure 2.

Facing the challenges of oilfield development, such as high requirements for model robustness and interpretability, constructing a dual-driven model with knowledge and data could improve the accuracy and robustness of the model, and reduce the need for data.

$$L(\theta) = \lambda_{data} MSE_{data} + \lambda_{PDE} MSE_{PDE} + \lambda_{BC} MSE_{BC} + \lambda_{IC} MSE_{IC} + \lambda_{EC} MSE_{EC} + \lambda_{EK} MSE_{EK} \quad (1)$$

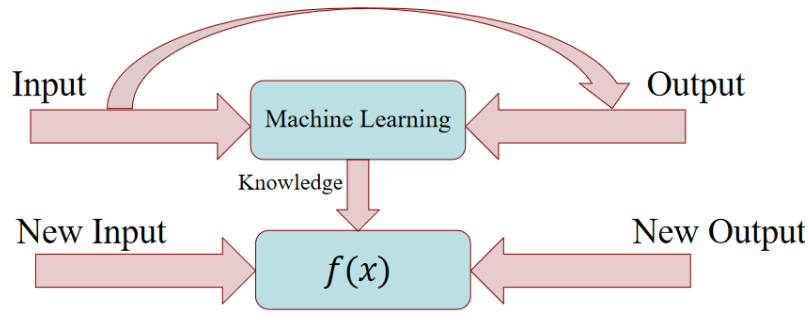


Figure 2. Traditional machine learning model

In 2019, RAISSI et al. [56] proposed Physically Informed Neural Networks (PINNs), which incorporated physical law constraint terms described by general nonlinear partial differential equations into neural network training. In 2020, PARK et al. [57] proposed a hybrid-driven neural network based on data and basic physical laws. This approach aimed to assist in production planning and dynamic decision-making for unconventional reservoirs in onshore basins within the United States. Chaoqin Huang et al. [58] proposed a new model for deep learning of seepage considering physical process information. The analysis showed that with the reduction of sample data, the new model with the addition of physical information could better maintain its accuracy and precision. Xue Liang et al. [59] established a deep neural network model for pressure field prediction jointly driven by reservoir seepage physics and data. The researchers incorporated the mathematical model of seepage into the loss function as regularization (as shown in formula 1). They observed that this approach led to a significant reduction in prediction errors.

4. Problems faced

In summary, machine learning has encountered the following problems in oil and gas exploration and development.

(1) The depth of application of machine learning in the oil and gas industry was still insufficient. Although the application of machine learning in the oil and gas industry is currently a trend and hotspot, the accuracy and generalization of the results that met the requirements of the actual industry were still a few. At the same time, many machine learning algorithms had strict constraints on the application conditions. It was often difficult to meet these conditions in the actual engineering problems. The accuracy of the final model or results could not meet the requirements of the actual engineering, which also made a lot of machine learning algorithms in the oil and gas industry not being applied.

(2) Data were difficult to obtain and could not be shared promptly. Many sample data were difficult to obtain. There were missing values in the collected data, while the source of data had a certain degree of uncertainty. Although the amount of data was large, there was a lack of communication and sharing. The data could not be fully utilized and effectively processed, while many data had different sources. Besides, there was a lack of an integrated database and information exchange platform. Efficient data analysis and organization were the basic conditions for using machine learning algorithms, which was also the technology that needed to be solved and developed.

(3) Lack of compound talents. Many researchers in the field of machine learning did not know much about the oil and gas industry. They lacked relevant professional knowledge, so it was difficult to combine the actual situation in the field to propose effective and applicable models. Staff in the oil and gas field also lacked an understanding of machine learning, and it was difficult to provide applicable data. That made it difficult for machine learning researchers to apply appropriate algorithms and build models. Effective communication and exchange between personnel in the two fields could not take place. Therefore, the lack of composite talents was also a limitation for the current wide application of machine learning in the oil and gas industry.

5. Future prospects

This paper reviews the application of machine learning in oil and gas exploration and development. It puts forward the following prospects and suggestions to accelerate the application of machine learning in oil and gas exploration and development.

(1) Construct a shared database to enhance data interoperability and governance. Combine with the Internet of Things, data cloud, and other technologies to establish a digital information exchange platform. It could upload a variety of the latest data and achieve unhindered data communication. Strengthen data measurement technology, improve the certainty of data sources, and break the problem of difficult data access. Promote the link between data measurement sensors and databases. Then the data obtained from measurements could enter the database at the earliest time for use.

(2) Establish an intelligent integrated simulation test platform. The platform was capable of automatic model fitting and trend prediction of data in real-time to give scientific program optimization. The establishment of this platform could greatly save the repetition cost in the application process of machine learning in the oil and gas industry and realize the intelligent union of data and algorithms.

(3) Conduct regular training to cultivate compound research talents. Through the joint efforts of schools and enterprises to provide students with the latest industry data and learning opportunities. Then enterprise personnel could get professional guidance and training. That strengthened the deep integration of academia and promoted the transformation of scientific and technological achievements. Only this, can we cultivate composite talents who understand both the knowledge of the oil and gas industry and machine learning.

References

- [1] KUANG Lichun, LIU He, REN Yili, et al. Application and development trend of artificial intelligence in petroleum exploration and development [J]. Petroleum Exploration and Development, 2021, 48 (1): 1 - 11.
- [2] H.B. Li, P.Y. Luo, Y.Y. Bai, et al. Overview of machine learning algorithms and their application in drilling engineering [J]. Xinjiang Oil and Gas, 2022, 18 (1): 1 - 13.
- [3] HANG Dongxiao, CHEN Yuntian, MENG Jin. Well logging curve generation method based on recurrent neural network [J]. Petroleum Exploration and Development, 2018, 45 (04): 598 - 607.
- [4] Pham N, Wu X, Naeini E Z. Missing well log prediction using convolutional long short-term memory network [J]. Geophysics, 2020, 85 (4): 1 - 55.
- [5] YANG Jing, CHEN Yuntian, JIANG Chunbi. A machine learning modeling paradigm for the logging curve generation problem - an example of shale wells in Changning Weiyuan area [J]. China Offshore Oil and Gas, 2020, 33 (01): 76 - 84.
- [6] BITTAR M, WANGS, WUX, et al. Multiple well-log depth matching using deepQ-Learning [J]. Petrophysics-The SPWLA Journal of Formation Evaluation and Petrophysics-The SPWLA Journal of Formation Evaluation and Reservoir Description, 2021, 62 (4): 353 - 361.
- [7] ZHOU Xin, CAO Junxing, WANG Xingjian et al. Reconstruction technique of acoustic logging curve based on two-way gated recurrent unit neural network [J]. Advances in Geophysics, 2022, 37 (01): 357 - 366.

- [8] CACERES VAT, DUFFAUTK, YAZIDIA, et al. Automated well-log depth matching:1Dconvolutional neural networks vs. classic cross correlation [J]. *Petrophysics*, 2022, 63 (1): 12 - 34.
- [9] TENG Jianqiang, QIU Meng, YANG Mingren, et al. Well log curve prediction method based on gated recurrent unit neural network [J]. *Oil and Gas Geology and Recovery*, 2023, 30 (01): 93 - 100.
- [10] WU X, LIAN, L, SHI Y, et al. Deep learning for local seismic image processing: fault detection, structure-oriented smoothing with edge preserving, and slope estimation [R]. and slope estimation by using a single convolutional neural network [R]. San Antonio: 2019 SEG Annual Meeting, 2019.
- [11] PHAN S, SEN M. Deep learning with cross-shape deep Boltzmann machine for pre-stack inversion problem [R]. San Antonio: 2019 SEG Annual Meeting, 2019.
- [12] MA Y, CAO S, RECTOR J W, et al. Automatic first arrival picking for borehole seismic data using a pixel-level network[R]. San Antonio: 2019 SEG Annual Meeting, 2019.
- [13] Qin Min, Hu Xiangyang, Liang Yunan, et al. Identification of high-temperature and high-pressure reservoir fluids using Stacking model fusion method [J]. *Petroleum Geophysical Exploration*, 2021, 56 (02): 364 - 371+214 - 215.
- [14] CHEN Yan, JIAO Shixiang, CHENG Chao, et al. A semi-supervised compartmentalized interlayer identification method based on self-coder [J]. *Specialty Oil and Gas Reservoirs*, 2021, 28 (01): 86 - 91.
- [15] Y. Zhang, R.W. Ding, S. Zhao et al. A denoising method for shallow stratigraphic profiles based on improved loop generation adversarial network [J]. *CTheoretical and Applied Research*, 2023, 32 (01): 15 - 25.
- [16] CHEN Juan, ZHANG Yanduo, LU Tao. A rock-like crack detection method based on pixel difference convolutional neural network[J]. *Journal of Wuhan Engineering University*, 2023, 45 (01): 81 - 86+100.
- [17] CHENG Guojian, GUO Wenhui, FAN Pengzhao. Rock image classification based on convolutional neural network [J]. *Journal of Xi'an Petroleum University (Natural Science Edition)*, 2017, 32 (04): 116 - 122.
- [18] CHENG Guojian, LI Bi, WAN Xiaolong et al. Research on rock flake image classification based on Squeeze Net convolutional neural network [J]. *Mineral Rock*, 2021, 41 (04): 94 - 101.
- [19] LI Liang, XUE Yuan, GAO Yuan et al. Research on the quality control method of exploration and development data based on machine learning [J]. *Information System Engineering*, 2021 (04): 146 - 147+150.
- [20] WU Fan, FANG Zhendong, XIAO Lizhi. Application of offshore multi-source logging data in reservoir capacity prediction [J]. *Petrochemical Technology*, 2022, 29 (01): 145 - 148.
- [21] Liu GQ, Gong RB, Shi YJ, et al. Construction of oil and gas formation logging knowledge map and its intelligent recognition method [J]. *Petroleum Exploration and Development*, 2022, 49 (03): 502 - 512.
- [22] Mudan, Wang Zhuwen, Huang Yulong et al. Volcanic lithology identification based on SVM logging data-an example from the eastern depression of the Liao he Basin [J]. *Journal of Geophysics*, 2015, 58 (05): 1785 - 1793.
- [23] Li JG, Zhang WD, Liu GN. Application of deep learning in logging lithology identification [J]. *Science and Technology Innovation and Application*, 2015 (14): 21 - 22.
- [24] An Peng, Cao Danping. Research and application of deep learning-based lithology recognition method for logging [J]. *Advances in Geophysics*, 2018, 33 (03): 1029 - 1034.
- [25] JIANG Kai, WANG Shoudong, HU Yongjing et al. Well logging lithology identification model based on Boosting Tree algorithm [J]. *Logging Technology*, 2018, 42 (04): 395 - 400.
- [26] Feng Yaxing, Gong Xi, Xu Yongyang et al. Research on lithology recognition method based on rock fresh surface image and twinned convolutional neural network [J]. *Geography and Geographic Information Science*, 2019, 35 (05): 89 - 94.
- [27] C. Y. Wu, X. Zhang, C. L. Zhang et al. A lithology identification method based on LSTM recurrent neural network [J]. *Lithologic reservoirs*, 2021, 33 (03): 120 - 128.
- [28] Zhang Chi, Pan Mao, Hu Shui-Qing et al. A machine-learning lithology identification method for fusing reservoir longitudinal information[J]. *Geoscience and Technology Bulletin*, 2023, 42 (03): 289 - 299.

- [29] HOU Mingyu, YANG Jianqin, LI Weichong. Research on lithology identification based on graph embedding technology [J]. China Petroleum and Chemical Standards and Quality, 2023, 43 (13): 169 - 171.
- [30] Jicai Ding. Quantitative prediction method of reservoir physical properties based on support vector machine [C]//Chinese Geophysical Society, Organizing Committee of National Symposium on Petrology and Geodynamics, Tectonic Geology and Geodynamics Specialized Committee of Chinese Geological Society, Regional Geology and Mineralization Specialized Committee of Chinese Geological Society. 2015 Proceedings of the Joint Academic Conference of the Geosciences of China (XX) - -Topic 51 Reservoir Geophysics. China Peace Audio and Video Electronic Press, 2015: 3.
- [31] Ni Weijun, Li Qi, Guo Wenhui et al. Transverse wave velocity prediction of shale reservoir based on support vector machine [J]. Journal of Xi'an Petroleum University (Natural Science Edition), 2017, 32 (04): 46 - 49+54.
- [32] ZHU Linqi, ZHANG Chong, ZHOU Xueqing et al. A prediction method of reservoir permeability in NMR logging by fusing deep confidence network and with kernel limit learning machine algorithm [J]. Computer Applications, 2017, 37 (10): 3034 - 3038.
- [33] LIN Nian-Tian, ZHANG Dong, ZHANG Kai et al. Small-sample convolutional neural network learning and prediction of seismic oil and gas reservoirs [J]. Journal of Geophysics, 2018, 61 (10): 4110 - 4125.
- [34] YU H Y, REZAEI R, WANG Z L, et al. A new method for TOC estimation in tight shale gas reservoirs [J]. International Journal of Coal Geology, 2017, 179: 269 - 277.
- [35] TANG Cheng, WANG Chongjing, LIANG Bo et al. Research on the calculation model of shale gas evaluation parameters based on machine learning algorithm [J]. Recorded Well Engineering, 2021, 32 (04): 18 - 22.
- [36] ZHANG Yuhang, SHI Baohong, ZHANG Yujing et al. Application of machine learning method in porosity prediction of shallow beach-dam phase thin reservoirs--an example of Cretaceous system in Chepaizi area, Junggar Basin[J]. Journal of Sedimentology, 2023, 41 (05): 1559 - 1567.
- [37] Xiao Ai, Hongyu Wang, Baitao Sun. Automatic Identification of Sedimentary Facies Based on a Support Vector Machine in the Aryskum Graben. Kazakhstan [J]. Applied Sciences, 2019, 9 (21).
- [38] XIAO He, ZHANG Chaomu, SU Xiangqun. Application of logging data to quantitatively identify carbonate sedimentary microphases--A case study of Changxing Formation in Yuanba area, northeast Sichuan [J]. Science, Technology and Engineering, 2020, 20 (07): 2573 - 2582.
- [39] Liu X Y, Zhou L, Chen X H, et al. Lithofacies identification using support vector machine based on local deep multi-kernel learning [J]. Petroleum Science, 2020 (4).
- [40] Chen Li, Wang Caizhi, Ning Qianqian et al. Recognition method based on machine learning for petrographic logging of Long7 section in Longdong area of Ordos Basin [J]. Reservoir Evaluation and Development, 2023, 13 (04): 525 - 536.
- [41] Liu Zongbao, Cui Yumeng, Li Junhui et al. Convolutional neural network-based lithologic type logging curve recognition in dense sandstone reservoirs [J]. Journal of Heilongjiang University of Science and Technology, 2023, 33 (03): 376 - 383.
- [42] Wang Yanping, Jiang Jing, Dang Jingwen et al. An introduction to the dynamic analysis of oil and gas well production [J]. China Petroleum and Chemical Standards and Quality, 2021, 41 (15): 29 - 30.
- [43] Tian ZX. Application of machine learning in reservoir production dynamic analysis [D]. China University of Geosciences (Beijing), 2022.
- [44] GU Jianwei, ZHOU Mei, LI Zhitao et al. Data mining-based well production prediction method for long and short-term memory network model [J]. Specialty Oil and Gas Reservoir, 2019, 26 (02): 77 - 81+131.
- [45] LIU Wei, LIU Wei, GU Jianwei. Daily oil production prediction of oil wells based on machine learning method [J]. Oil Drilling Process, 2020, 42 (01): 70 - 75.
- [46] Xue L, Gu Shaohua, Wang Jiabao et al. Dynamic prediction of gas well production based on particle swarm optimization and long- and short-term memory neural networks [J]. Oil Drilling Process, 2021, 43 (04): 525 - 531.
- [47] Xue YC, Yuan ZQ, Jin QS et al. Well production prediction based on deep forest algorithm [J]. Science, Technology and Engineering, 2022, 22 (11): 4327 - 4334.

- [48] Han Yidong. Capacity prediction of volumetrically fractured horizontal wells in tight reservoirs based on machine learning [D]. Northeast Petroleum University, 2023.
- [49] Yao J, Zhang K, Liu JR. Theory and application of intelligent oilfield development [M]. Qingdao: Science Press, 2018: 48 - 51.
- [50] Du, Yuqi, Weiss, et al. "Obtain an Optimum Artificial Neural Network Model for Reservoir Studies." Paper presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, October 2003. presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, October 2003.
- [51] L. Zhang, X. S. Chen, G. X. Li, et al. An automatic history fitting method based on ensemble and neural network architecture search [J]. Journal of China University of Petroleum: Natural Science Edition, 2022, 46 (2): 127 - 136.
- [52] LU Yi, HU Hao, CHENG Yabin, et al. Research on automatic history fitting method for reservoir simulation with multiple models [J]. Journal of Southwest Petroleum University: Natural Science Edition, 2022, 44 (6): 97 - 104.
- [53] Lee, Sanghyun, and Karl, Dunbar Stephen. "Field Application Study on Automatic History Matching Using Particle Swarm Optimization." paper presented at the SPE Reservoir Characterization and Simulation Conference and Exhibition, Abu Dhabi, UAE, September 2019.
- [54] Santoso, Ryan, He, et al. "Bayesian Long-Short Term Memory for History Matching in Reservoir Simulations." Paper presented at the SPE Reservoir Simulation Conference, On-Demand, October 2021.
- [55] Vo Thanh, Hung, Sugai, et al. "Integrated Artificial Neural Network and Object-based Modelling for Enhancement History Matching in a Fluvial Channel Sandstone Reservoir." Paper presented at the SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition, Bali, Indonesia, October 2019.
- [56] RAISSI M, PERDIKARIS P, KARNIADAKIS G E. Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations [J]. Journal of Computational Physics, 2019, 378: 686 - 707.
- [57] PARK J, DATTA-GUPTA A, SINGH A, et al. Hybrid physics and data -driven modeling for unconventional field development and its application to US onshore basin [J]. Journal of Petroleum Science and Engineering, 2021, 206: 109008.
- [58] HUANG Chaoqin, NIAN Kai, WANG Bin, et al. A new model for deep learning of hydrocarbon seepage considering physical process information [J]. Journal of China University of Petroleum: Natural Science Edition, 2020, 44 (4): 47 - 56.
- [59] Xue L, Dai C, Han Jiangxia et al. Deep neural network modeling driven by combined reservoir seepage physics and data [J]. Oil and Gas Geology and Recovery, 2022, 29 (01): 145 - 151.