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Investigating the Frontiers of Deep Learning and Machine Learning: A Comprehensive Overview of Key Challenges in Missing Well Log Estimation

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***Abstract* - Well logging is a significant method of geological formation description and resource assessment in the exploration and development of oil, natural gas, minerals, groundwater, and sub-surface thermal energy, as well as geotechnical engineering and environmental research. However, the challenging problem of estimating well logging data always exists because well logs can only be measured through a drilling process involving costly and time-consuming field trials. This study provides a brief overview of Deep Learning (DL) models and examines the well-logging issues in estimating missing well-log data. In addition, it discusses a literature review focusing on the application of DL models for well-log estimation. The outcome of this exploratory work necessitates suitable requirements for the design and implementation.**

Keywords: Artificial intelligence, Data sparsity, Deep learning, estimation, Machine learning, Well logging.

I. INTRODUCTION

Well log is the continuous measurement of well responses to logging tools. It is a record of the geological formations (that is, physical properties) of a well (borehole) (Yang *et al.* 2023). Well logging records the practice of the geologic formations along a borehole (Avseth *et al.*, 2013; Feng *et al.*, 2018). This is a field technique used in mineral exploration to gather and analyze the geologic formations which a drill hole had passed through (Farrag *et al.*, 2019; Carrasquilla and Lima, 2020; Marzan *et al.*, 2021; Lai *et al.*, 2022).

Investigating the frontiers of well-log estimation has many benefits, including extracting the detailed records of geologic formations, survey of geotechnical and other environmental studies which will be interpreted and used to obtain the associated rock and fluid properties of the well. These and the associated analysis can then be used to infer further properties such as hydrocarbons saturation and formation pressure and to make further drilling and production decisions. Moreover, well logging provides real-time evaluation of the formation characteristics. This information can be effectively used for correcting the borehole drilling schedules. For example, if the depth of target formation is different from the expected depth, well logs can be used for assessing this flaw and take corrective measures in real time. Well logging estimation to reservoir characterization presents particular difficulties because of its interpretation and analysis, which calls for creative solutions. The oil and gas industry and the larger fields of deep learning and machine learning both benefit from the efforts made to comprehend and explore the boundaries of well-log estimation.

The objectives of this study are to elucidate or explain all the related works in well logging carried out with the assistance of DL, to discuss the most important issues related to the computational processing of DL and ML with reference to oil exploration, and to highlight current research efforts in estimating missing well log data as well as future research trends. Though, literatures have revealed in the past that, there have been limited researches on the intersection of ML and DL. Even till today, only a small amount of work has been reported on the application of cutting-edge/innovative DL technologies, in the context of reservoir characterization and subsurface formation determination within AI. For instance, Lai *et al.* (2023) explored the application of well log in overcoming the challenging issues such as fracture detection and characterization, which is dependent on a combination of core, well-logs and seismic data. The authors only provided a literature survey about DL approaches and neglected to provide a comparative study of different DL approaches and related issues. In contrast, Karnowski *et al.* (2010) provided a significant review of DL models and methods that are used to handle various tasks in well logs even though the research work exploits various DL models sufficient details, the authors discussed about various popular models such as the Convolutional neural networks, stacked auto-encoder, hierarchical temporal model and deep belief neural network with some popular application areas of DL.

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This current trend has led us to conduct a comprehensive investigation to evaluate the current status of deep learning methodologies in this field. By comparing the different DL architectures that are available, we hope to identify the effects on model performance and help future researchers better understand the benefits and drawbacks of these architectures. The study's primary contributions are to give background information and explain the taxonomy and variations of well-known DL models, look into how DL models affect and are significant for the most common ML tasks, especially machine translation, and list and discuss the limitations, difficulties, and new developments in the field of DL and ML

This study has significant consequences for DL and ML researchers and practitioners. By giving an in-depth summary of the state-of-the-art and emphasizing significant difficulties and emerging trends, the paper can assist readers in developing a better understanding of the field, which may guide future research by giving them a path forward to explore novel avenues and get around obstacles. Moreover, the paper's insights into the potential applications of DL and ML may have an impact on the creation of new technologies and applications in oil exploration field. In the same vein, the findings or outcome of this study have significant consequences for figuring out new trends in the DL and ML fields.

Future researchers may find these insights useful in understanding the progress made in pre-trained language models and their language processing abilities. It is anticipated that the models will carry out tasks that are similar to those of humans, including question-answering, understanding and evaluating input, summarizing texts, translating languages, and more. For readers who are interested in DL and ML, this paper offers several important takeaways. First, it presents a comprehensive summary of the dominant advancements in DL and ML, emphasizing important issues and new directions, which is extremely important for researchers who want to stay up to date on the latest developments in their field. Overall, the paper's main conclusions focus on the field of oil exploration that provides difficulties of estimating missing well log data in the context of reservoir characterization, and the prospects for future study and advancement of DL and ML.

II. LITERATURE REVIEW

2.1 Origin and Development of Geophysical well Logs

According to Allaud and Martin (1977) and Ellis and Singer (2007), well logging was created in 1927. Geophysical well logging was first introduced in 1927 when the Schlumberger brothers and Henri Doll measured the first resistivity curve at Pechelbronn (Allaud and Martin, 1977; Luthi, 2001; Ellis and Singer, 2007). Since then, well logs have been widely used in the geophysical, engineering, and geological fields (Ellis and Singer, 2007). In addition to core and seismic data, well logs provide continuous distribution, low cost, and high vertical resolution by continuously measuring the petrophysical parameters (acoustic, electrical, and nuclear) of the borehole (Ellis and Singer, 2007; Aghli *et al.*, 2016). Since its inception in France in 1927, well logging has experienced significant and ongoing changes with several timelines (Tiab and Donaldson, 2005). Luthi (2001) enumerates the history of well-logging development which can be split into four separate phases.

At the conception phase, the recording of petrophysical properties with wirelines is crucial to comprehending the geological features of the subsurface formation. During this phase, electric well logging was invented in 1927 (Luthi, 2001). There is a lot of widely used logging tools developed at this point. When gamma-ray logging was first implemented in the late 1930s, it was used to distinguish between clean and shale formations (Ellis and Singer, 2007). Schlumberger debuted the first dipmeter instrument in 1942 (Luthi, 2001). Then, in 1955, the Schlumberger Company started working in velocity logging (Ellis and Singer, 2007). Since it could be used with oil-based drilling muds, the induction logging tool, which was first introduced in the 1940s, has quickly spread and taken over the resistivity survey market as a whole (Liu, 2017). On the other hand, saline drilling fluids employ laterolog-style tools. Developed in 1960, the deep-induction measurement (ILd) is still used today (Ellis and Singer, 2007). The year 1948 saw the introduction of the neutron logging tool, which consisted of a single detector recording the "neutron count rate" and a chemical neutron source.

Furthermore, Schlumberger Company joined the velocity logging industry in 1955, while the induction logging tool gained popularity in the 1940s for its use in oil-based drilling muds. Laterolog tools are used in saline drilling fluids, and deep-induction measurement (ILd) is still in use today (Ellis and Singer, 2007). Moreso, Neutron logging was introduced in 1948 with a chemical neutron source and a single detector for counting neutrons. Neutron logs were used to calculate porosity and determine hydrocarbon type. Well logs are increasingly used for correlation, zone identification, surveying, and perforating (Bateman, 2020). Thereafter, Schlumberger developed electrical measurements in the 1950s, including micro resistivity and neutron porosity logs. Induction logging was proven feasible for freshwater or oil-based mud. The dual laterolog was introduced in 1972, providing two laterolog measurements and a resistivity measurement. Similarly, density logs and sidewall neutron porosity tools were also introduced in the 1960s. Which was put in commercial use? Again, the sidewall neutron porosity

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(SNP) was introduced in 1962, and then the compensated neutron logging tools (CNL) were introduced in the late 1960s (Luthi, 2001).

The NMR effect was discovered in 1946 and NMR logging started in the 1960s, becoming available in the market in 1991. It is widely used for porosity, permeability, and fluid property analysis (Liu, 2017). Subsequently, the borehole televiewer (BHTV) was developed by Mobil Corporation in the late 1960s, providing borehole images to measure the four micro resistivity curves, two caliper curves, and three azimuth curves. The high-resolution dip meter (HDT) was introduced in 1967 to determine stratigraphic dip. Logging-while-drilling (LWD) was introduced in the 1980s. The 1980s saw the introduction of logging-while-drilling (LWD), in which log curves are recorded while drilling (Luthi, 2001). the introduction of porosity and resistivity logs, along with other novel petrophysical logging techniques like BHTV, SHDT, and NMR logs, have broadened the use of well logs in geological domains. Well-logging has been redefined as a crucial tool for reservoir development and management due to several technological advancements (Luthi, 2001).

The reinvention phase (1985–2000): Up until the 1970s, all well-log recordings were made using analog systems, and the logs were made on paper using an ink pen or with a light beam on photographic film (Bateman, 2020). Moreover, well log data became digital starting in the 1980s. During the rebirth phase, two significant advancements occurred in the 1990s: the first was the introduction of multi-array induction tools, or devices with multiple simple arrays (Ellis and Singer, 2007), and the second was the introduction of an imaging logging tool by Schlumberger (Formation Micro-Imager tool, or FMI) in 1991, which is the successor to the FMS (Formation MicroScanner) tool, which was developed in the 1980s, and its introduction signifies the start of a new era in well logging technology (Lai *et al.*, 2018). During the 1990s, NMR logging emerged as a reliable wireline measurement method (Luthi, 2001). The capacity to detect thin layers has also been enhanced by the multi-array induction tools, which have increased the vertical resolution of logs from 1 m (dual lateral logs have a vertical resolution of 1 m) to 1-2 feet (0.3048 m–0.6096 m). The FMI imaging logging tool can gather 192 microresistivity curves because it has 192 electrodes and 8 pads. Afterwards, high-resolution images (up to 5 mm) of the wellbore wall can be created by processing the microresistivity curves (Lai *et al.*, 2018; Lai *et al.*, 2022).

Today, modern borehole geophysical logging methods were created in the twenty-first century to offer fine-grained information on petrophysical characteristics like fluid property, mineralogy, and reservoir quality. The image logs can be used to identify the geological objects (vugs) that are 5 mm or larger.

2.2 Current State of well-log estimation

The process of forecasting subsurface rock and fluid properties through indirect measurements obtained during drilling operations is known as well log estimation. Gamma-ray, resistivity, neutron porosity, density, and sonic velocity are a few examples of the measurements that can be made. Well-log estimation is currently done using both cutting-edge technologies and conventional methods. The following are some significant facets of well log estimation as it stands today.

2.2.1 Conventional Techniques

This involves history matching. It is the procedure for comparing the reservoir simulation model with the observed data and adjust the uncertain parameters in the simulation model to reduce its mismatch with the observed data. Conventional history matching could be considered as a different method (Li *et al.*, 2020). This technique is otherwise referred to as a hybrid/mix between deterministic and non-deterministic approaches.

2.2.2 Empirical Equations

The correlation analysis is a conventional method used in finding the complex relationship between two types of data. Moreover, the correlation between the two types of data cannot be expressed through the use of some simplified linear relationship but should include the exponential, logarithmic, and other nonlinear mapping relationships (Wang *et al.*, 2016). Moreover, Zhu *et al.* (2022) and Sabouhi *et al.* (2023) opined that the presence and provision of a well logging data often provides comprehensive petrophysical information and seismic data, which are valuable for the characterization and evaluation of the strata Therefore, there is tendency to have an interrelationship (i.e., correlation) between the two types of data. Since many well-log estimates are still based on statistical analyses of well-log data from related geological formations, empirical equations are still frequently used. The properties of interest are directly related to the measured log responses by these equations.

2.2.3 Petrophysical Models

Geostatistical (GS) methods are methods used in estimating petrophysical logs (e.g., sonic logs), independently and in combination with empirical petrophysical relations (PRs). The geostatistical method examines the data distribution, trends, directional components as well as outliers of geological parameters across the reservoir (Ringross and

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Bentley, 2015). They use variograms which describes the degree of spatial dependence between sample values on separation distance (lag). Mirhashemi *et al* .(2022) employed geostatistical method to estimating petrophysical logs, particularly the sonic logs, independently and in combination with empirical petrophysical relations (PRs) and the methods evaluated. To estimate formation properties like porosity, permeability, and fluid saturation, physicists employ a variety of petrophysical models. These models include geological information, core measurements, and well log data.

2.2.4 Manual Interpretation

This method is used to determine lithology, assess reservoir quality, estimate fluid types, and evaluate other properties of the formation; proficient petrophysicists manually interpret well logs. This procedure entails applying geological principle knowledge and analyzing log response patterns.

2.2.5 Machine Learning

This method involves the use of Supervised Learning, where labeled well log data is used to train machine learning algorithms, including regression, decision trees, and neural networks, to predict formation properties. These models are capable of processing massive amounts of data and capturing intricate connections between various log measurements. In the same vein, the unsupervised Learning which is without labeled examples, clustering algorithms can find patterns and groupings in well log data. This can be useful in determining subsurface anomalies, reservoir zones, and lithology classes. Furthermore, Deep Learning where convolutional neural networks (CNN) and recurrent neural networks (RNNs), two types of deep neural networks, are being used more and more for well log interpretation tasks. These models are capable of capturing temporal dependencies and learning hierarchical representations of log data. All things considered, well log estimation as it exists today improves accuracy, efficiency, and risk management in subsurface characterization for oil and gas exploration and production by fusing traditional knowledge with cutting-edge technologies like machine learning, data analytics, and digital tools.

AI, a term coined by John Mc Carthy is a branch of Computer Science that studies how to endow computer with the capability of human intelligence. This has however led to the evolvement of various methods and techniques of solving human, natural complex tasks with the intention or purpose of creating machines or system that mimic some or all of the inherent features underlying them. Thus, an upsurge of works in AI have brought about good evaluation of machines that can now perform complex tasks in an intelligent manner to that extent, there has emerged several paradigms of AI, including NLP, knowledge representation, expert systems and others. In fact, it is part of the extensive domain of data science and integrates traditional programming with machine learning (ML), the latter featuring methodologies such as deep learning (DL) and artificial neural networks (ANN) (Figure 1).

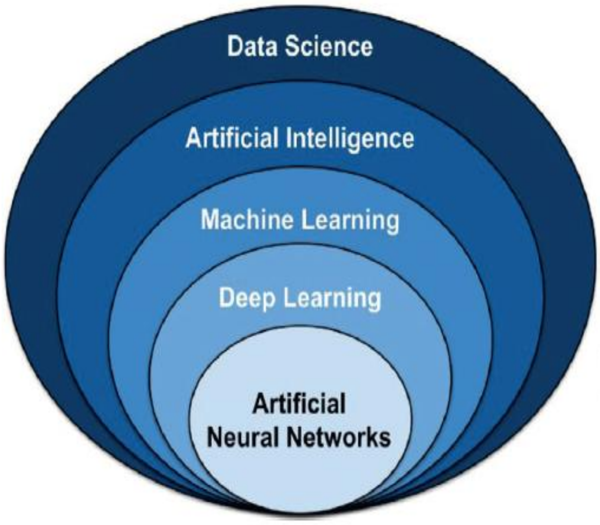

Figure 1: The close connection and overlap between the fields of machine learning, deep learning, and artificial intelligence

Machine learning has branched out of AI and thus focused with the development of computational methods for learning and building systems that behave intelligently. These algorithms address real life challenges especially classification, regression and prediction problems using the supervised, unsupervised and reinforced learning methods by employing different algorithms like SVM, KNN, RF, DT, deep Adversarial network, and other algorithms (Ezugwu *et al.*, 2023).

Artificial Intelligence (AI) has found a wide spread use in making the complex decision-making procedures simple in virtually all economic market field, and oil and gas upstream industry is no exception to it. AI involves the use of sophisticated networking tools and algorithms in addressing complex problems in such a way that mimic human intellect, with the aim of enabling computing devices to carry out tasks that could earlier be carried out by humans. Unlike other simpler automations that are computational in nature, AI enables the designed tools to "learn" through repeated tasks, thereby continuously refining the computing capabilities as more data is fed into the system (Bello *et al.*, 2016).

Recently, AI has led to meaningful designing and computation optimizations in the global Petroleum Exploration and Production (E&P) industry, and its applications have only continued to grow with the introduction of modern drilling and production technologies.

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Tools such as Artificial Neural Networks (ANN), Genetic Algorithms, Support Vector Machines and Fuzzy Logic have a historic connection with the E & P industry for more than 16 years now, with the first application dated in 1989 for development of an intelligent reservoir simulator interface, and for well-log interpretation and drill bit diagnosis through neural networks. Computational tools (devices and programs) have been proposed to bridge the technology gaps hindering automated execution and monitoring of key reservoir simulation, drilling and completion procedures including seismic pattern recognition, reservoir characterisation and history matching, permeability and porosity prediction, PVT analysis, drill bits diagnosis, overtime well pressure-drop estimation, well production optimization, well performance projection, well / field portfolio management and quick, logical decision making in critical and expensive drilling operations. The paper reviews and analyses this successful integration of AI techniques as the missing piece of the puzzle in many reservoir, drilling and production aspects.

Furthermore, AI enables geoscientists and engineers to analyze vast amounts of data from seismic surveys, well logs, and production records to identify potential drilling locations, predict reservoir characteristics, optimize well design, and maximize hydrocarbon recovery. Some of the earliest applications of AI in drilling engineering include the use of expert systems for drilling decision-making and neural networks for drilling parameter prediction. For instance, during the early 2000s, the use of data mining techniques, such as neural networks, became more prevalent in drilling engineering. During the drilling operations, the presence of trouble zones or harder formations might result in problems like kicks, loss of circulation, or even damage to the bit used. Hence, identifying the lithology during drilling is a key factor in assuring successful drilling operations. One way to predict lithology during drilling operations is using logging while drilling (LWD) (Li *et al.*, 2020). LWD tools usually include a GR log which is an important tool in lithology identification (Sun *et al.*, 2019). However, a major difficulty encountered with the LWD tools is that it is located several feet above the drill bit behind a rotary steerable system. This might lead to an entire formation being drilled before the LWD sensors reach it which would be too late in case of trouble formations. That is the reason why the need would be favourable to have a tool that enables lithology identification at the bit itself. Artificial intelligence (AI) and machine learning, computational models can be developed to predict certain parameters from readily available drilling data in real-time without well intervention. Different AI techniques such as ANN, ANFIS, FN, Random Forest, and support vector machine (SVM), have been applied in the oil and gas industry (Aly, *et al*., 2021).

Consequent to the ever-increasing need to accurately model reservoir parameters and constant development of better techniques for reservoir characterization and uncertainty analysis, artificial intelligence (AI) has become the tool of choice evident in several automation systems. Machine learning has branched out of AI and thus focused with the development of computational methods for learning and building systems that behave intelligently. Machine learning is an application of Artificial Intelligence based upon giving machines data to learn from and then make predictions or decisions. The trend of soft computing in reservoir and uncertainty modelling will continue to rise (Wong, *et al.*, 2013). Machine learning can be divided into supervised, unsupervised and reinforcement learning. These algorithms address real life challenges especially classification, regression and prediction problems using the supervised, unsupervised and reinforced learning methods by employing different algorithms like SVM, KNN, RF, DT, deep Adversarial network, and other algorithms (Arigbe, 2020; Ezugwu *et al.*, 2023).

Today, DL and AI techniques are being extensively employed for carrying out oil exploration tasks (Yang et al., 2023). Venugopalan *et al.*, (2014) put forward combined deep neural network architecture, particularly the Convolutional neural network and recurrent network (CNN-RNN) for translating video into sentences. The authors modeled every frame of the video using a CNN. The CNN was trained using more than 1.2 million images with categorical labels. When it comes to the application of RNN, it has been pre-trained on more than 100,000 photos from Flickr and COCO with matching sentence captions to represent the semantic state and word sequence. To address the shortcomings of its conventional phrase-based translation system, Google recently unveiled neural machine translation (NMT), a novel automated machine translation system (Wu *et al.*, 2016). Two recurrent networks form the foundation of the suggested NMT system. While the second RNN produces the translated output text, the first RNN's task is to process the input text sequence.

2.3 Deep Learning

Deep learning (DL) has become a new and innovative area of study within machine learning research (Hinton and Salakhutdinov, 2006). Previously, delving or investigating into the parameter space of deep architectures presented a number of difficulties, but more recently, advances in DL algorithms have effectively tackled or confronted this issue, resulting in noteworthy advances in a variety of domains (Du and Shanker, 2009). DL is sometimes referred to as feature learning, deep-structure learning, and representation learning in literature. The primary feature of representation learning is its capacity to allow machines to process raw data and

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automatically extract the representations that are needed for tasks like detection or classification. In the same vein, it is a subfield of machine learning and artificial intelligence, that is, an area of study within artificial intelligence and machine learning that includes a range of algorithms developed from artificial neural networks (ANNs). Moreover, DL has demonstrated impressive performance on a variety of natural language understanding tasks. These results have advanced the field significantly and have been highly anticipated (LeCun *et al.*, 2015). DL algorithms come in two flavors: supervised and unsupervised. However, the characteristics of DL approaches include managing multiple levels of representation; non-linearity; the ability to learn from raw data directly; and scalability.

2.3.1 Convolutional Neural Net

Convolutional neural net (CNNs) was introduced in 1998 by researchers like Bengio, Le Cun, Bottou, and Haffner (LeCun *et al.*, 1998). The CNNs are a unique kind of multi-layer neural network that is purposefully structured to handle and analyze two-dimensional data A CNN is a choice of topology or architecture that leverages spatial relationships to reduce the number of parameters which must be learned and thus improves upon general feed-forward back propagation training. CNNs were proposed as a deep learning framework that is motivated by minimal data preprocessing requirements. (Arel *et al.*, 2010). The back propagation algorithm is used to achieve look-alikes for almost all previous neural networks and training (Arel *et al.*, 2009). Their first convolutional neural network, LeNet-5, was able to distinguish between handwritten and regular digits. CNN models have been widely used in many different applications and scenarios, particularly in image and video processing tasks. With their exceptional capacity to identify important features and evaluate visual data, CNNs are now indispensable for applications like deep generative modelling and video analysis. It is beyond computer vision; CNNs' adaptability has shown value in speech recognition and other fields.

The convolution layers, which make up the first two layers of the CNN, are primarily responsible for extracting features from input. The dense part, which is the fully connected layer uses the information from the convolution layer, the fully connected layer generates output similar to other conventional neural networks as CNN is trained through the use of forward and backward propagation techniques as depicted in Figure 2. From raw data, CNNs can immediately identify patterns without the need for further preprocessing. Another benefit of CNNs is their resilience to noise and geometric distortions, such as shifts in scale, angle, and shape. Despite these aberrations, CNNs successfully finish tasks involving object segmentation, recognition, and detection. The ability of neural networks to derive spatial information from pictures is its ability. The connected layers process their data twice using both linear and non-linear transformation methods. But for complex tasks, only linear transformation may not be capable as the CNNs have several activation functions like Sigmoid, tanh, RELU, linear and soft max to work with.

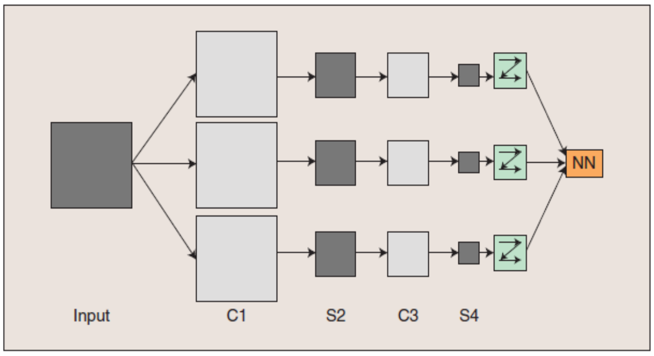

Figure 2: Conceptual example of convolutional neural network

2.3.2 Deep neural networks

Many layers of non-linear operations are stacked together to form deep neural networks (Hinton and Salakhutdinov, 2006). Both supervised and unsupervised learning techniques leave their mark on DNN. DNN employs supervised algorithms to generate output from the outcomes of unsupervised algorithms and uses RBMS and auto encoders to extract features in an unsupervised manner.

2.3.3 Deep belief networks

Deep belief networks (DBNs) were first proposed by Hinton et al. (2006) [35]and are members of the generative model's family. DBNs address problems encountered when traditionally applying back-propagation to deeply layered neural networks, namely: (1) necessity of a substantial labeled data set for training, (2) slow learning (i.e., convergence) times, and (3) inadequate parameter selection techniques that lead to poor local optima. DBNs are composed of several layers of Restricted Boltzmann Machines, a type of neural network (see Figure 3). These networks are "restricted" to a single visible layer and single hidden layer, where connections are formed between the layers (units within a layer are not connected). The hidden units are trained to capture higher-order data correlations that are observed at the visible units.

DBNs are arguably the most widely used class of neural networks (NNs) since they are essentially an architecture similar to NNs but with a faster learning mechanism. When simple networks like autoencoders or RBMs are stacked on top of one another, DBN is created (Arel *et al.*, 2010; Hamel and Eck, 2010; Hinton *et al.*, 2006). DBN is limited to

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numerous hidden layers and one bottom-level visible layer. These models have been inspired by sources such as (Marr, 1983), which attempt to map various computational phases in image understanding to areas in the cortex. Over time these models have been refined like the Hierarchical Temporal Memory (HTM).

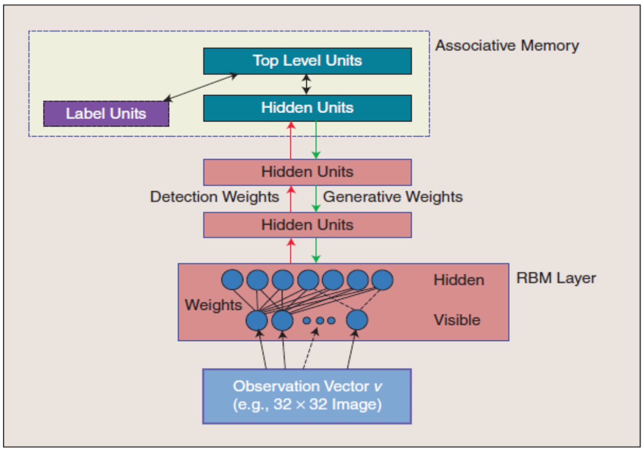

Figure 3: Illustration of the Deep Belief Network framework

2.3.4 Recurrent Neural Network (RNN)

RNNs are members of the family of artificial neural networks. Recursive edges between units make up an RNN's internal structure, which takes information persistence into account. They are able to exhibit historical performance that is propelling because of this. This flaw is addressed by RNNs, which use memory and condition the output of each algorithm iteration on features derived from previous iterations, especially "long-distance" prior iterations. RNNs have been used for a variety of tasks, including text generation, image captioning, speech recognition, translation, language modeling named entity recongition, and text generation (Sutskever *et al.*, 2014; Karpathy and Fei-Fei, 2015; Serizel and Giuliani, 2016; Luong *et al.*, 2015; Bonadiman *et al.*, 2015).

III. RELATED WORKS

A number of recent researches have been conducted in the new aspects of the petrophysical characterizations. For instance, Convolutional Neural Network (CNN) is one of the intelligent methods that can characterize the desired factors in porous media. Al- Fattah *et al.* (2001) used Artificial neural network in the production of gas considering several input parameters such as GDP growth rate, footage drilled, wells drilled, annual depletion, gas prices and other resources. Xu *et al.* (2015) and Salem *et al.* (2018) in their separate work used Back propagation for the production of liquid and oil by taking into account the various factors such as Temperature, heat, superficial gas velocity, and superficial liquid velocity. However, Xu *et al.* (2015) addresses the number of open wells and the new production wells with treatment using factors such as monthly injection production ratio; kernel function; number of open injection wells, newly opened production wells, and old wells with efficient treatment. Zhang *et al.* (2014) used graph neural network with improved Particle Swarm optimization method to produce liquid in the estimation of the water saturation level. Salem *et al.*, (2018) used the diagenesis, deep; GR log; neutron log; density log; sonic log; deep resistivity log Porosity to determine the permeability and porosity in a way of determining the well logs. Gaurav, (2017) used ANN for determining the oil production using the horizontal permeability; porosity as input parameters. Ghahfarokhi *et al. (*2018) determined the level of gas production using flowing time, distributed temperature sensing distributed acoustic sensor as its parameters.

Liu *et al.* (2021) applied laboratory measurements on core samples by integrating nuclear magnetic resonance (NMR) and CT scan technology to describe pore structure in coal. Golsanami *et al.*, (2020) established a relationship between elastic module and Archie's coefficients based on Particle Flow Code (PFC3D) coring to geomechanical characterization in a fractured carbonate reservoir. In another research, Golsanami *et al.*, (2021) determined pore types in a carbonate reservoir using NMR log and deep learning and assessed compressional wave velocity response through seismic attributes, porosity, and permeability. Furthermore Smith (2007) employed cross–plot methods using two resistivity logs comprising, spherically focused log (SFL) and deep penetrating induction (ILD) with sonic log (DT), provided a method to estimate non recorded sonic log. Other studies used porosity to compute the unknown sonic logs. Koroteev and Tekic (2020) applied geological assessment using non-gradient optimization and interpolation techniques for the automatic mapping of reservoir rocks over an oil region, here, the use of this method speed u; the manual process of mapping procedure, thus improve its accuracy. In subsequent task, the authors used Gradient Boosting, deep neural network and other several machine learning and its combination algorithms for extracting information logs from the well log data. This current study work employed Supervised Learning algorithms such as Support Vector Machine, for both estimating missing logs and uncertainty reduction across log, core and well test permeability due to its ability to perform well with irregular and smaller number of data mainly due to its kernel function and other hyperparameters. Other algorithms like Decision tree and Linear regression were also tried. Their results were compared with both existing and developed empirical models.

Joshi *et al.*, (2021) investigated the challenge of cost and tiresome encountered during the process of using the conventional way of evaluation well logs. In their effort to

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achieve a reduced time in evaluating logs, the authors proposed a novel approach to predict sonic log, adopting a regression method using a supervised machine learning (ML) algorithm, along with the determination of lithology employing clustering and a neural network approach, which is grounded on the basis of gamma-ray log values and hence creating a correlation between the two.

Wang *et al.*, (2022) investigated the challenge of preserving previous information of well logs. In the work, the authors proposed a model for classifying and predicting long term sequence well log data using deep learning integrated neural network with the self-attention mechanism. The authors opined that Deep learning (DL) technology provides new possibilities for accurate missing well logs prediction. According to the authors, DL is a newly developed machine learning (ML) algorithm in artificial intelligence that can extract high-level features of input data by constructing a multilayer network. The authors stated that Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are DL techniques that is widely used in prospecting geophysical data processing and interpretation. Moreover, the CNNs model offers some advantages, such as shared convolution kernels and automatically extracted features though it has received widespread attention in its use in geophysical exploration, including full-waveform inversion, dispersion curve picking, and seismic data classification.

Zhu *et al.*, (2022) investigated the challenge of obtaining low accuracy from the use of conventional or traditional method of preserving the well logs. In their attempt to accomplish the objective of maintaining the correctness of the well logs, the authors proposed model for generating the missing logging curves of horizontal wells in the shale gas reservoirs, with a view to facilitate the exploration and development of unconventional reservoirs

Wang *et al.*, (2021) addressed the problem of missing and damaged or distorted well log data in old oilfields due to shutdowns, poor borehole conditions, damaged instruments and so on. Though, the authors stated in their assertions that well logging helps geologists to discover hidden oil, natural gas and other resources. Well log data are however, systematically insufficient because they can only be obtained by drilling, which involves costly and time-consuming field trials. The authors proposed a spatio-temporal neural network (STNN) algorithm, which is built by leveraging the combined strengths of a convolutional neural network (CNN) and a long short-term memory network (LSTM). The STNN exploits the ability of the CNN to effectively extract features related to pseudo-well log data and the ability of the LSTM to extract the key features from well log data along the depth direction. The STNN method allows full consideration of the well log data trend with depth, the correlation across different log series and the actual depth accumulation effect. The method adopted proved successful in predicting acoustic sonic log data from gamma-ray, density, compensated neutron, formation resistivity and borehole diameter logs. Results showed that the proposed method achieves higher prediction accuracy because it takes into account the spatio-temporal information of well logs.

Shan *et al.*, (2021) investigated the problem of measuring well logs through drilling process, which is always costly and time-consuming. The authors used bidirectional long short-term memory (BiLSTM), attention mechanism, and convolutional neural network (CNN), which were coupled or combined together to build hybrid neural networks for predicting missing well logs. Moreover, traditional machine learning models, CNN, BiLSTM, and other deep learning benchmark models were developed to compare with the presented models. Results show that the proposed method achieves higher prediction accuracy because it takes into account the spatio-temporal information of well logs.

Qiao *et al.*, (2022) investigated the challenge of missing well logs. In the study, the authors stated that the prediction of missing well logs is an effective way to reduce the exploratory expenses and as a result of the complexity and heterogeneity of the reservoirs, there must be strong nonlinear correlations between the well logs. In an effort to address the problem, the authors proposed a method based on a Bayesian optimized hybrid kernel extreme learning machine (BO-HKELM) algorithm to improve the accuracy and stability of the missing well logs prediction.

Several research have in one way or the other experiment used machine learning algorithms to estimate missing well logs such as acoustic logs (AC), density logs (DEN), and gamma ray (GR) from available well logs (Gowida *et al.*, 2019: Gowida, 2020). Fung *et al.*, (1997) provide a reasonable approach to forecast permeability and porosity logging curves from existing well logs by constructing a back propagation neural network (BPNN) model. For improving the prediction performance, the genetic algorithm was introduced to optimize the hyperparameters of artificial neural networks (ANNs) for well logging reconstruction (Mo *et al.*, 2015). Rolon *et al.*, produced synthetic well logs by using general regression neural network (GRNN) and achieved a better performance by comparing the proposed method with multiple regression (Rolon *et al.*, 2009). It has been proved that the task of the logging prediction is particularly suitable for ANNs.

Nevertheless, the application of the conventional ANNs have been discovered to have quite a few known deficiencies in the training process, such as bad local minima, poor

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generalization performance, and slow convergence speed, which restricts the prediction performance of well logs (Gharbi and Mansoori, 2005). To address the problem posed by the application of ANN, a deep belief network was introduced to realize the porosity log prediction (Duan *et al.*, 2018). DBN has unique advantages in initializing the weight matrix of the network and can greatly shorten the training time. Akinnikawe et al. found that random forest (RF) is superior to ANN (Akinnikawe *et al.*, 2018). They used ANN, support vector machine (SVR), random forest (RF), decision trees (DT), and gradient boosting (GB) to generate conventional logging data from existing well logs. He *et al.*, (2019) addressed the problem of estimating the field strength of parameters of rock in drilling process. The authors employed a deep convolutional neural network (DCNN), which is conventionally based on the stochastic pooling method and softmax loss.

Zhang *et al.*, (2018) used a random forest (RF) machine learning model to estimate mechanical properties of rock formations. The model was trained using data from multiple boreholes and achieved an accuracy of 89.6% in predicting mechanical properties. Shi *et al.*, (2021) proposed a deep learning method based on a convolutional neural network (CNN) to estimate the rock mechanical properties from drilling data. The proposed model achieved a mean absolute percentage error (MAPE) of 5.12% for Young's modulus and 5.92% for Poisson's ratio, respectively. Han *et al.*, (2020) developed a hybrid model combining a k-nearest neighbor (KNN) algorithm and an artificial neural network (ANN) to predict the missing mechanical properties of rocks. The model achieved an accuracy of 86% in predicting the missing data. Yang *et al.*, (2019) proposed a hybrid algorithm based on a clustering method and a support vector machine (SVM) to estimate the rock mechanical properties from drilling data. The model achieved an accuracy of 90.5% in predicting Young's modulus and 93.3% in predicting Poisson's ratio. *Li et al.*, (2020) proposed a hybrid model that combines principal component analysis (PCA) and a support vector machine (SVM) to estimate missing rock mechanical properties. The model achieved an accuracy of 92.1% in predicting missing data.

Zheng *et al.*, (2021) investigated the shortage of well-logging data, which can only be measured by expensive and time-consuming field tests. In an attempt to achieve the goal of finding an effective method of addressing the well log prediction taking into consideration the spatio-temporal attributes of the well log data, the authors employed a machine learning approach. Moreover, a convolutional neural network (CNN) and the long short-term memory (LSTM) neural networks were combined to extract the spatial and temporal features of well-logging data, and the particle swarm optimization (PSO) algorithm was used to determine hyperparameters of the optimal CNN-LSTM architecture to predict logging curves in this study.

Zheng *et al.*, (2020) investigated the challenge encountered in estimating missing logs due to instrument failure. The author proposed a deep learning-based technique that combines a CNN and LSTM without incurring an expensive cost of relogging. In the experiment conducted, the CNN layer is employed to extract depth series features at the initial point before they imputed to the LSTM to improve the feature memory and extraction capabilities of LSTM.

Alizadeh *et al.*, (2021) addressed the problem of shear wear velocity indirect relation to the soil dynamic property as well as the issue of cost, which limits the amount of downhole seismic data generated. The authors proposed an ensemble system for estimating the shear velocity using the limited available data. The ensemble of neural network (2D and 3D) models ware designed and developed while a feed forward neural network (FFNN).

IV. CHALLENGING ISSUES IN THE ESTIMATION OF MISSING WELL LOG DATA IN OIL EXPLORATION

In the field of geoscience and reservoir engineering, estimating well logs plays a crucial role in understanding subsurface properties, optimizing resource extraction, and making informed decisions in the oil and gas industry. Well logs provide valuable information about rock formations, fluid properties, and reservoir characteristics. However, one of the significant challenges faced in this domain is the sparsity of data, which hinders the accurate estimation of missing well log values. This section delves into the intricacies of data sparsity as a key challenge and explores strategies to address this issue using advanced machine learning techniques.

Data Sparsity refers to the situation where a large portion of the dataset contains missing or incomplete values. In the context of well logs, sparsity arises due to various factors such as drilling conditions, data acquisition limitations, sensor failures, and operational constraints. For instance, certain depths or intervals in a well may lack recorded log data, leading to gaps in the dataset. The sparsity of data poses a significant hurdle in building robust models for estimating missing well log values accurately. The sparsity of data in well logs presents several challenges that impact the reliability and effectiveness of estimation models (Yang *et al.*, 2023).

1) *Limited Training Data:* Sparse datasets often result in limited training samples for machine learning models. This scarcity of data can lead to overfitting, where the model memorizes noise rather than learning meaningful patterns, affecting the generalization capability. Consequently, data

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sparsity can lead to biased prediction and unreliable results. Therefore, the estimation of missing well logs enables the completion of dataset thus, allowing for a more comprehensive analysis. Data imbalance, which is a similar challenging issue to data sparsity in that the well log data often suffer from class imbalance where certain classes or categories of well logs are underrepresented. This can lead to biased model that perform poorly on minority class.

2) *Inaccurate interpolation:* Interpolating missing well log values becomes challenging in sparse datasets, especially when the available data points are widely spaced or discontinuous. Traditional interpolation methods may yield inaccurate results, compromising the quality of estimation.
3) *Uncertainty quantification:* uncertainty is the extent to which predicted values deviates from measured data. With respect to reservoir characterization, it is reservoir modelers best estimate of how a modelled reservoir quantity might deviate from the true value of that quantity. Thus, the challenge of the oil and gas industry is to accurately characterize reservoir parameters that are difficult due to these uncertainties. This is because every analysis starts with the measurement of the degree of uncertainty inherent/intrinsic in the determination of/ identification of the reservoir rock properties to determine if the rock formation is consolidated, semi-consolidated or unconsolidated based on the data available. As a result, sparse data introduces higher uncertainty in estimation outcomes, as there are fewer data points to support predictions. Quantifying and managing this uncertainty is crucial for making reliable decisions based on estimated well log values.
4) *Feature engineering and selection:* This is one of the phases involved in the process of estimating missing well logs. It is the stage where engineers are concerned with the identification, extraction and selection of relevant features from the well log data that will be used as inputs to the machine learning models to improve the performance. Feature engineering involves a routine check, data standardization and the partitioning of dataset into training dataset and testing dataset. The routine check for this stage is always achieved through the visualization of the distribution of the features before deciding on the inclusion of the data transformation to improve the model's estimation performance as discussed and applied in similar task (Mehedi *et al.*, 2022). Additionally, the sparse datasets may lack sufficient examples to identify relevant features for log estimation accurately. Hence, selecting the right set of informative features that captures important geological information while avoiding irrelevant redundant data becomes more challenging, leading to suboptimal model performance.
5) *Model complexity:* The design of deep and Machine learning model can effectively learn and generalize from complex well log data is non-trival. This is because balancing model Complexity to avoiding overfitting or underfitting is essential for robust missing well log estimation.
6) *Evaluation Metrics:* The choosing of appropriate evaluation metric for assessing the performance of missing well-log estimation is another challenging issue. This is because, in most experiments, four predictive metrics are computed to assess the performance of the prediction results of well logs, namely root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and person correlation coefficient (PCC). These evaluation metrics indicate the deviation of prediction of proposed models. Others metrics like Pearson correlation matrix, MSE are avoided by researchers in usage because it is claimed to be ambiguous (Chatterjee *et al.*, 2013). Hence, metric aforementioned needs to be carefully selected based on the specific application and objective of the experiment.
7) *Interpretation issues:* This arises from the subjective nature of geological and petrophysical interpretation estimation of missing well logs involves extrapolating trends, assumptions and inferring relationship based on the limited data introduces biases and uncertainties such as facies change, structural complexities and depositional environment further complicate the interpretation process.

V. CONCLUSION

These days ML and DL are two high-focus of data science. DL models for automatic text analysis and disambiguation (advanced modelling technique and robust data management) have sprung up outstandingly in the last decade. The exercise of DL for advanced modelling technique and robust data management as well as interpretation analysis in the ML/DL research domain arouses intense research interest. The succeeding years of DL-based modelling can be reverberant, once the myths around it are dispelled.

In this article we tried to provide a comprehensive detail about neural networks, detail about how NN transformed into convolutional networks and in turn how CNNs networks are turned into DBN, and finally how DL models evolved from traditional networks. Additionally, we have also provided details about its various DL architectures such as CNN, DBN, RNN, and LSTM networks. Finally, the researchers have provided a detailed analysis of major DL tasks in which DL models such as DBN, CNN, and RNN are successfully applied and set the new state-of-the-art results in ML/DL areas such as oil exploration, appraisal, drilling and production. The performance of DL models seems auspicious, however, the

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results talked over in this study are exploratory from some subfields of ANN. In this study, the main focus of this study was on the investigation of various challenging issues in the estimation of missing well log data in oil exploration and various ML/DL models, including CNNS, DBN, RNN, GRU, and LSTM networks, which are applied to subsurface characterization tasks.

From the discourse of the various models, the paper concluded that (a) despite the application of conventional ANNs advanced capabilities in estimating and predicting accurate and reliable result of missing well logs, ANN models, which are trained on massive amounts of numerical data using statistical learning techniques, still face significant challenges such as bad local minima, poor generalization performance, and slow convergence speed in comprehending and appropriately using its functions to prediction/estimate the performance of well logs (b) Firstly, data quality is crucial because the accuracy and reliability of DL models depend on the quality of data that they are trained on. DL models learn from patterns in data, and if the data is noisy, poor, incomplete, inconsistent in format or biased, the models can learn and perpetuate these same problems. Hence, it is crucial to guarantee the utilization and robust management of high-quality data during the training of DL models, minimizing errors and ensuring its representative nature in capturing real-world phenomena that the models aim to grasp. Secondly, data diversity is critical because DL models need to be exposed to a broad range of examples and variations to learn robust representations that generalize well to new data. If the training data is too narrow or limited in scope, the models may not be able to handle new and unseen inputs, leading to poor performance and generalization. By incorporating a diverse range of data sources, a DL model can learn a broad range of patterns and relationships, making it more adaptable to new situations and environments. For deep learning models, the importance of data quality and diversity is even more pronounced. These models necessitate robust data management strategies, data integration techniques and quality control measures. Establishing data standards, enhancing data acquisitions technologies and implementing data validation procedures are essential in mitigating data related challenges thus generating accurate and reliable performance of models. Additionally, interpretation issues which arises from the subjective nature of geological and petrophysical interpretation of missing well logs will require the incorporation of multiple lines of evidence, expert knowledge and uncertainty quantification techniques for the interpretation workflow.

In conclusion, estimating missing well log is challenging yet essential task in subsurface characterization and reservoir modelling. Overcoming these challenges require multidisciplinary approach that combines advanced modelling techniques, robust data management practices and rigorous interpretation methodologies. By addressing the technical, data-related and interpretation challenges, research can improve the accuracy, reliability and utility of estimated well logs. Continued advancement in technology data integration, and collaboration research efforts will further enhance the ability to characterize subsurface reservoirs effectively and support sustainable energy development.

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