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Research Article

Examining the Boundaries of Machine Learning and Deep Learning: A Thorough Review of the Main Obstacles in Missing Well Log Estimation

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Abstract:
In geotechnical engineering, environmental research, and the discovery and extraction of minerals, oil, natural gas, groundwater, and subsurface thermal energy, well logging is an essential technique for describing geological formations and evaluating resources. However, since well logs can only be measured through a drilling process that involves expensive and time-consuming field testing, computing well logging data is a challenging issue that will never be solved. This paper investigates the well-logging problems in predicting missing well-log data and gives a quick introduction to Deep Learning (DL) models. It also talks about a review of the literature that focuses on employing DL models for well-log estimation. As a result of this exploratory effort, appropriate design and implementation requirements are required.

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

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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 can then be used, together with the related studies, to further infer attributes like formation pressure and hydrocarbon saturation, and to guide future drilling and production decisions. Furthermore, well logging offers an instantaneous assessment of the properties of the formation. The borehole drilling schedules can be properly corrected with the usage of this information. For instance, well logs can be used to evaluate flaws and make real-time corrections if the target formation's depth deviates from the expected depth. Because of its interpretation and analysis, well logging estimation to reservoir characterisation has unique challenges that require innovative solutions. The endeavours to comprehend and investigate these concepts serve not only the oil and gas business but also the broader fields of deep learning and machine learning. The well-log estimation's bounds.

This study's goals are to clarify or explain all related well logging projects that used DL assistance, to talk about the most crucial problems pertaining to DL and ML computational processing in the context of oil exploration, and to highlight ongoing and upcoming research initiatives in the area of estimating well log data that is missing. However, previous literature has indicated that little research has been done on the junction of ML and DL. As of right now, not much research has been published on the use of state-of-the-art/innovative deep learning technologies for AI subsurface formation identification and reservoir characterisation. As an example, (Lai et al. 2023) investigated how well logs may be used to address difficult problems like fracture characterisation and identification, which rely on a combination of seismic, well-log, and core data. The authors failed to include a comparative analysis of various DL approaches and associated problems, and instead just offered a scan of the literature on DL approaches. Conversely, (Karnowski et al. 2010) offered an important overview of DL models and techniques that are used to different tasks in well logs. even though the study makes use of a variety of DL models With adequate detail, the writers talked on a number of well-known models, including deep belief neural networks, stacking auto-encoders, hierarchical temporal models, and convolutional neural networks, along with some well-known DL application fields.

We've conducted a thorough analysis to assess the state of deep learning approaches in this industry as a result of the present trend. We aim to determine the impact on model performance and assist future researchers in comprehending the advantages and disadvantages of the various DL architectures that are accessible by comparing them. The main contributions of the study are providing background information, elucidating the taxonomy and variations of popular DL models, investigating the effects of DL models on and significance for popular ML tasks, particularly machine translation, and enumerating and debating the challenges, obstacles, and recent advancements in the field of DL and ML.

Researchers and practitioners working in DL and ML will be greatly impacted by this study. The paper can help readers gain a better understanding of the field by providing an in-depth summary of the state-of-the-art and highlighting important challenges and emerging trends. This can help guide future research by providing a path forward to explore new avenues and overcome obstacles. Furthermore, the paper's observations about the possible uses of DL and ML may influence the development of fresh tools and software for the oil exploration industry. Similarly, this study's results have important ramifications for identifying emerging patterns in the DL and ML domains.

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.

LITERATURE REVIEW

Origin and Development of Geophysical Well Logs

The assertion that well logging originated in 1927 is made by (Ellis and Singer 2007) as well as (Allaud and Martin 1977). Henri Doll and the Schlumberger brothers measured the first resistivity curve at Pechelbronn in 1927, which is when geophysical well logging was first used (Allaud and Martin, 1977; Luthi, 2001; Ellis and Singer, 2007). According to Ellis and (Singer 2007), well logs have been extensively employed in the geophysical, engineering, and geological domains ever since. Well logs continually measure the petro physical parameters (acoustic, electrical, and nuclear) of the borehole in addition to seismic and core data, offering continuous distribution, cheap cost, and high vertical resolution (Ellis and Singer, 2007; Aghli et al., 2016). Well logging has had significant and on-going changes since its founding in France in 1927, according to numerous timelines (Tiab and Donaldson, 2005). (Luthi 2001) enumerates the evolution of well-logging history, which can be separated into four main phases.

Wireline recording of petrophysical data is crucial during the conception stage to comprehend the geological properties of the underlying formation. Electric well logging was invented in this age in 1927 (Luthi, 2001). Currently, a large number of widely used logging tools have been developed. Gamma-ray logging was first applied in the late 1930s to distinguish between shale and clean deposits (Ellis and Singer, 2007). Schlumberger debuted the first dipmeter apparatus in 1942 (Luthi, 2001). Then, in 1955, the Schlumberger Company started utilising velocity logging (Ellis and Singer, 2007). Because the induction logging instrument may be used with oil-based drilling muds, Since its first publication in the 1940s, this product has grown to become the industry leader in resistivity surveys (Liu, 2017). Conversely, tools in the laterolog style are used with saline drilling fluids. Developed in 1960, the deep-induction measurement (ILd) is still in use today (Ellis and Singer, 2007). The first neutron logging apparatus was developed in 1948 when a chemical neutron generator and a single detector that measured the "neutron count rate" were coupled.

Furthermore, because oil-based drilling muds employed the induction logging device, it became more and more common in the 1940s. A company called Schlumberger entered the velocity logging market in 1955. Saline drilling fluids are utilised with lateralolog devices, and deep-induction measurement (ILd) is still employed today (Ellis and Singer, 2007). Furthermore, using a chemical neutron generator and a single neutron detector, the first neutron logging system was created in 1948. Hydrocarbon kind and porosity were determined using neutron logs. Surveying, correlation, zone identification, and perforating are among the growing uses of well logs (Bateman, 2020). Afterwards, in the 1950s, Schlumberger created electrical measurements, such as neutron porosity logs and micro resistivity logs. When it comes to freshwater or oil-based mud, induction logging has been shown to be effective. The dual laterolog, which provides resistivity measurement in addition to two laterolog measurements, was developed in 1972. Similarly, density logs and sidewall neutron porosity sensors were also introduced in the 1960s. Which was put to use for commercial reasons? To reiterate, compensatory neutron logging tools (CNL) were introduced in the late 1960s, after sidewall neutron porosity (SNP) was initially introduced in 1962 (Luthi, 2001).

1946 saw the discovery of the NMR effect, and NMR logging got underway in the 1960s before becoming widely accessible in 1991. Among its frequent applications are fluid property analysis, permeability, and porosity (Liu, 2017). Then, Mobil Corporation developed the borehole televiewer (BHTV) in the late 1960s, which offered borehole images for measuring the four micro resistivity curves, two calliper curves, and three azimuth curves. The high-resolution dip meter (HDT) was introduced in 1967 to determine stratigraphic dip. Logging-while-drilling (LWD) was initially used in the 1980s. The practice of "logging-while-drilling" (LWD), in which drillers record log curves, was initially used in the 1980s (Luthi, 2001). the application of resistivity and porosity logs along with additional state-of-the-art petrophysical logging techniques including NMR, BHTV, and SHDT logs, have expanded the use of well logs in geological fields. Well-logging has been redefined as a crucial tool for reservoir development and management as a result of several technological advancements (Luthi, 2001).

The reinvention era (1985–2000): Prior to the 1970s, when analogue techniques were employed, all well-log recordings were made on paper using an ink pen or a light beam on photographic film (Bateman, 2020). Furthermore, in the 1980s, well log data began to be digitalised. During the 1990s rebirth phase, two significant developments occurred: first, multi-array induction tools (Ellis and Singer, 2007) were introduced, which are devices with multiple simple arrays; second, Schlumberger introduced the Formation Micro-Imager tool (FMI), an imaging logging tool, in 1991. With the advent of this tool, a new era in well logging technology began, replacing the Formation MicroScanner tool, which was developed in the 1980s (Lai et al., 2018). In the 1990s, NMR logging became a dependable wireline measurement technique in the 1990s (Luthi, 2001 This tool, which was developed in the 1980s, replaced the Formation MicroScanner tool, ushering in a new age in well logging technology (Lai et al., 2018). According to (Luthi 2001), NMR logging developed into a trustworthy wireline measurement method in the 1990s. Additionally, thin layer detection has become more accurate because to the multi-array induction tools. With regard to the logs specifically, the vertical resolution has increased from 1 m (the vertical resolution of the dual lateral logs is 1 m) to 1-2 feet (0.3048 m–0.6096 m). The FMI imaging logging device can record 192 microresistivity curves because it has eight pads and 192 electrodes. The wellbore wall can then be captured in high-resolution images, with a resolution of up to 5 mm, by processing the microresistivity curves (Lai et al., 2018; Lai et al., 2022).

In the twenty-first century, advanced techniques for geophysical logging in boreholes were developed to provide detailed data on petrophysical attributes such as mineralogy, fluid property, and reservoir quality. Any geological object (vug) that is 5 mm in diameter or bigger can be identified using the picture logs.

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.

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.

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.

Petro physical Models

When calculating petrophysical logs (such as sonic logs), geostatistical (GS) approaches are employed both separately and in conjunction with empirical petrophysical relations (PRs). The distribution of data, trends, directional components, and outliers of geological parameters throughout the reservoir are all examined by the geostatistical method (Ringross and Bentley, 2015). The degree of geographical dependency between sample values on separation distance (lag) is described by variograms, which they employ. In order to estimate petrophysical logs, namely the sonic logs, (Mirhashemi et al. 2022) used a geostatistical method both alone and in conjunction with empirical petrophysical relations (PRs) and the methodologies examined. Physicists use a range of petrophysical models to estimate features of the formation like as porosity, permeability, and fluid saturation. Well log data, core measurements, and geological information are all included in these models.

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.

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, encompassing expert systems, NLP, knowledge representation, and other areas. It actually belongs to the broad field of data science and combines machine learning (ML), which uses techniques like artificial neural networks (ANN) and deep learning (DL), with classical programming Figure 1.

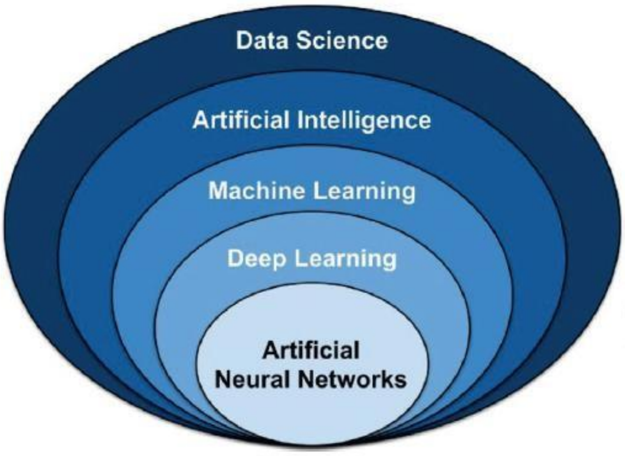

Figure 1. The close connection and overlap between the fields of machine learning, deep learning, and artificial intelligence

As a subfield of artificial intelligence, machine learning focuses on creating computational techniques for learning and creating intelligent systems. These algorithms use supervised, unsupervised, and reinforced learning techniques to address real-world problems, particularly those involving classification, regression, and prediction. They do this by utilising a variety of algorithms, including SVM, KNN, RF, DT, deep adversarial networks, and others (Ezugwu et al., 2023).

Artificial intelligence (AI) is being utilised to streamline complex decision-making processes in nearly every sector of the business. This also applies to the upstream oil and gas industry. Artificial intelligence (AI) is the application of cutting-edge networking technologies and algorithms to solve complex problems in a way that approximates human cognition, with the aim of enabling computing systems to perform tasks that could previously be accomplished by humans. Unlike other simpler automations that are computational in nature, artificial intelligence (AI) enables the generated tools to "learn" through repeated operations, so continuously refining the computing skills as additional data is fed into the system (Bello et al., 2016).

Artificial intelligence (AI) has recently made a substantial design and computation optimisation contribution to the global petroleum exploration and production (E&P) sector, thanks to the introduction of cutting-edge drilling and production technologies. Tools including Artificial Neural Networks (ANN), Genetic Algorithms, Support Vector Machines, and Fuzzy Logic have been used by the E&P industry for more than 16 years. These tools were initially used in 1989 for the creation of an intelligent reservoir simulator interface, well log interpretation, and neural network-based drill bit diagnosis. Computational tools (devices and programs) have been developed to solve the technology gaps prohibiting automated execution and monitoring of crucial reservoir simulation, drilling, and finishing procedures. These consist of the following: identification of seismic patterns, characterisation and history matching of reservoirs, prediction of permeability and porosity, PVT analysis, diagnostic of drill bits, assessment of overtime well pressure-drop, optimisation of well output, projection of well performance, and This paper looks at and assesses the successful application of AI techniques as the last element missing in several drilling, reservoir, and production-related domains.

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. In the early 2000s, for example, drilling engineering saw a rise in the application of data mining methods, such as neural networks. Harder formations or problematic spots could cause issues like circulation loss, kickbacks, or even damage to the bit being utilised during the drilling process. Therefore, a crucial element in guaranteeing the success of drilling operations is determining the lithology during the process. (As per Li et al. 2020), logging while drilling, or LWD, is one method of predicting lithology during drilling operations. According to (Sun et al. 2019), a GR log is a crucial instrument for lithology identification and is typically included in LWD kits. The fact that the LWD tools are hidden beneath a rotary steerable device several feet above the drill bit presents a significant challenge. In the event of difficulty formations, this could result in drilling through a formation entirely before the LWD sensors get there. For this reason, having a technology that allows for lithology detection at the bit itself would be beneficial. Computational models, machine learning, and artificial intelligence (AI) can be used to create real-time, well-intervention-free predictions of certain parameters from easily accessible drilling data. The oil and gas sector has used a variety of AI approaches, including support vector machines (SVM), ANN, ANFIS, FN, Random Forest, and FN (Aly et al., 2021).

As improved methods for reservoir characterisation and uncertainty analysis continue to be developed, artificial intelligence (AI) has become the preferred technology in many automation systems due to the increasing necessity to accurately estimate reservoir parameters. In machine learning, A branch of artificial intelligence, computational methods for learning and building intelligent systems are the main focus. Machine learning, an artificial intelligence application, is based on providing machines with data to learn from and utilise for judgements or predictions. According to (Wong et al. 2013), soft computing will gain popularity in reservoir and uncertainty models. There are three types of machine learning: reinforcement learning, unsupervised learning, and supervised learning. These algorithms employ supervised, unsupervised, and reinforced learning approaches. They also use multiple algorithms, to solve real-world issues, especially those involving classification, regression, and prediction, using techniques like SVM, KNN, RF, DT, deep adversarial networks, and others (Arigbe, 2020; Ezugwu et al., 2023).

According to (Yang et al. 2023), oil exploration tasks are now often completed using DL and AI techniques. Specifically, the combined deep neural network design for video-to-sentence translation suggested by (Venugopalan et al. 2014) is called CNN-RNN, or convolutional neural network and recurrent network. Each video frame was modelled by the authors using a CNN. The CNN was trained using more than 1.2 million images with classified classifications. To represent the word sequence and semantic state, RNN is utilised. With associated sentence subtitles, over 100,000 photos from COCO and Flickr have been used to pre-train it. In response to the shortcomings of their conventional phrase-based translation engine, Google has 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. The input text sequence is processed by the first RNN, and the translated output text is produced by the second RNN.

Deep Learning

Deep learning (DL) has become a fresh and cutting-edge subject of study within machine learning research (Hinton and Salakhutdinov, 2006). There have been a number of difficulties in the past when investigating or probing the parameter space of deep architectures; however, recent advances in deep learning algorithms have effectively solved or faced this issue, resulting in noteworthy breakthroughs across a variety of fields (Du and Shanker, 2009). Deep learning (DL) is sometimes referred to as feature learning, representation learning, and deep-structure learning in literature. The primary feature of representation learning is the machine's capacity to comprehend raw data and automatically extract the representations needed for tasks like detection or classification. Comparably, it is a field of research in machine learning and artificial intelligence that emphasises on various algorithms developed with artificial neural networks (ANNs). A division of artificial intelligence and machine learning. DL has also shown to be highly successful on a variety of natural language processing-related tasks. (LeCun et al. 2015) have noted that the research has advanced significantly and that these findings were much anticipated. DL algorithms with and without supervision are available. But deep learning (DL) algorithms are scalable, capable of handling several levels of representation, and show nonlinearity. They also allow for direct learning from raw data.

Convolutional Neural Net

Researchers including Bengio, Le Cun, Bottou, and Haffner introduced convolutional neural nets (CNNs) in 1998 (LeCun et al., 1998). CNNs are a special type of multilayer neural network designed specifically to process and evaluate two-dimensional data. A CNN is an architecture or topology that improves on general feed-forward back propagation training by using spatial relationships to minimise the amount of parameters that need to be learnt. CNNs were introduced as a framework for deep learning driven by the need for little data preparation. (Arel and others, 2010). For practically all prior neural networks and training, look-alikes are obtained using the back propagation approach (Arel et al., 2009). LeNet-5, their initial convolutional neural network, demonstrated handwriting recognition capability above conventional digits. CNN models are extensively utilised in a wide range of scenarios and applications, especially in jobs involving the processing of images and videos. CNNs are now essential for tasks like deep generative modelling and video analysis due to their remarkable ability to recognise significant features and assess visual input. Beyond computer vision, speech recognition and other domains have benefited from CNNs' versatility.

The primary job of the CNN's first two layers, referred to as the convolution layers, is to extract features from the input. Figure 2 illustrates how CNN is trained using forward and backward propagation techniques. The fully connected layer, or dense section, uses the information from the convolution layer to provide output that is comparable to that of other conventional neural networks. Raw data can be immediately analysed by CNNs to identify patterns; further pre-processing is not required. Another benefit of CNNs is their resilience to noise and geometric aberrations, including variations in scale, angle, and shape. Despite these anomalies, CNNs perform well on tasks involving object segmentation, recognition, and detection. Images can have their spatial information extracted by neural networks. To process their data twice, the linked layers use both linear and non-linear transformation algorithms. However, a simple linear transformation might not be enough for challenging jobs because CNNs can work with a range of activation functions, such as Sigmoid, Tanh, RELU, linear, and soft max.

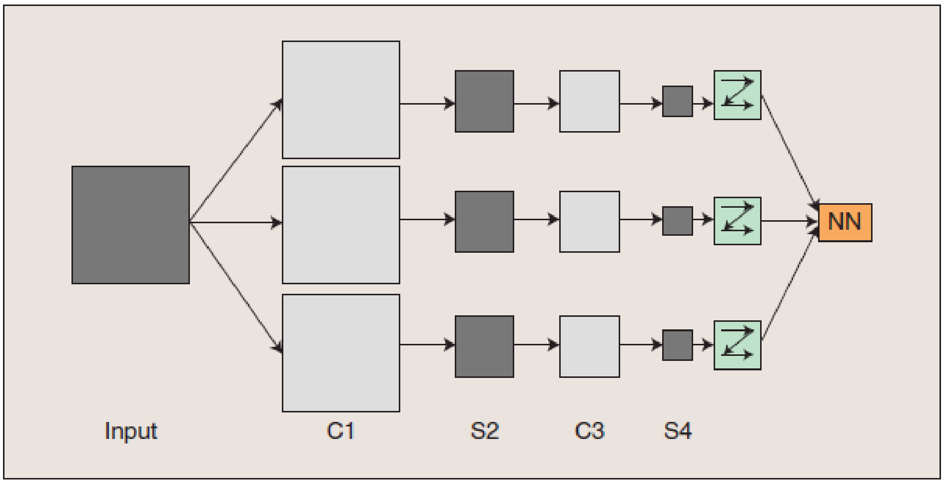

Figure 2. Conceptual example of convolutional neural network

Deep neural networks

Deep neural networks are composed of many layers of non-linear operations piled on top of one another (Hinton and Salakhutdinov, 2006). DNN is impacted by both supervised and unsupervised learning approaches. DNN uses supervised methods to produce output from the results of unsupervised techniques, and it uses auto encoders and RBMS for unsupervised feature extraction.

Deep belief networks

Deep belief networks (DBNs), which Hinton et al. (2006) first introduced, are a component of the generative model [35]. With back-propagation on conventionally deeply layered neural networks, three problems occur. These are addressed by Deeply Benevolent Networks (DBNs): (1) large labelled training data sets are needed; (2) learning (i.e., convergence) times are slow; and (3) subpar local optima are produced by ineffective parameter selection techniques. DBNs consist of several layers of a specific type of neural network known as Restricted Boltzmann Machines refer to Figure 3. These networks are restricted to one visible layer and one hidden layer. Within a layer, units are not connected to one another; instead, connections form between levels. Training occurs at the hidden units using higher-order data correlations seen at the visible units.

As DBNs are simply NNs with a quicker learning process, they could be the most widely used kind of neural networks (NNs). Autoencoders and RBMs are examples of simple networks that can be stacked on top of one another to create DBN (Arel et al., 2010; Hamel and Eck, 2010; Hinton et al., 2006). DBN is limited to numerous hidden layers and a single visible layer at the bottom. Based on studies like (Marr 1983), these models connect distinct cortical regions to various levels of computation involved in picture interpretation. Over time, other models have been refined, including the Hierarchical Temporal Memory (HTM).

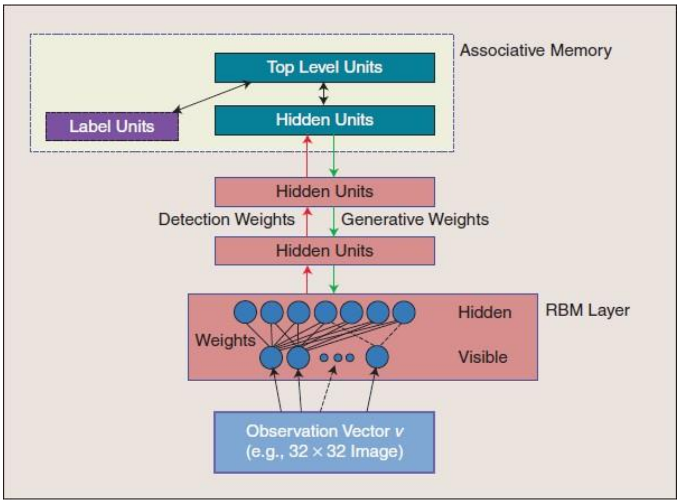

Figure 3. Illustration of the Deep Belief Network framework

Recurrent Neural Network (RNN)

RNNs belong to the artificial neural network family. An RNN's internal structure, which accounts for information persistence, is composed of recursive edges between units. As a result, they are able to offer historical performance that is inspiring. RNNs use memory to remedy this problem by conditioning each algorithm iteration's output on features derived from prior iterations, particularly "long-distance" prior iterations. Text generation, image captioning, speech recognition, translation, language modelling called entity recongition, and text generation are just a few of the tasks that RNNs have been applied to (Sutskever et al., 2014; Karpathy and Fei-Fei, 2015; Serizel and Giuliani, 2016; Luong et al., 2015; Bonadiman et al., 2015).

RELATED WORKS

Numerous studies in the novel facets of petrophysical characterisations have been carried out recently. One clever technique that can characterise the desired parameters in porous media, for example, is the Convolutional Neural Network (CNN). Artificial neural networks were utilised by (Al-Fattah et al. 2001) to produce gas while taking into account a number of input parameters, including GDP growth rate, dug wells' diameter, yearly depletion, gas prices, and other resources. Temperature, heat, superficial gas velocity, and superficial liquid velocity are only a few of the variables that (Xu et al. 2015) and (Salem et al. 2018) considered while using back propagation for the generation of liquid and oil. (Zhang et al. 2014) produced liquid in the calculation of the water saturation level using a graph neural network with an enhanced Particle Swarm optimisation technique. The diagenesis, deep resistivity log, GR log, neutron log, density log, sonic log, and (Salem et al. 2018) utilised Porosity as a means of figuring out the well logs by determining the permeability and porosity. (Gaurav 2017) employed artificial neural networks (ANN) with horizontal permeability and porosity as input parameters to calculate oil production. (Ghahfarokhi et al. 2018) used distributed temperature sensing, distributed acoustic sensor, and flowing time as its characteristics to determine the amount of gas production.

In order to characterise the pore structure in coal, (Liu et al. 2021) used nuclear magnetic resonance (NMR) and CT scan technology in conjunction with laboratory studies on core samples. A correlation was found by (Golsanami et al. 2020) between the Archie's coefficients and the elastic module in a fractured carbonate reservoir. This association was based on the PFC3D model of particle flow code coring. In a different study, (Golsanami et al., 2021) evaluated the compressional wave velocity response by utilising seismic characteristics, porosity, and permeability to identify the different types of pores in a carbonate reservoir, utilising NMR log analysis and deep learning. Additionally, (Smith 2007) used cross-plot techniques using two resistivity logs—the deep penetrating induction (ILD) with sonic log (DT) and the spherically focused log (SFL)—to generate an approximation for the non-recorded sonic log. Other research computed porosity using the unidentified audio logs . (Koroteev and Tekic 2020) used non-gradient optimisation and interpolation techniques to apply geological assessment for the automatic mapping of reservoir rocks over an oil region. By speeding up the manual mapping operation, this method improves accuracy. In the next assignment, the scientists extracted information logs from the well log data by combining different machine learning techniques, such as gradient boosting and deep neural networks, with data extraction. Because Support Vector Machine can perform well with irregular and smaller amounts of data primarily because of its kernel function and other hyperparameters, it was used in this study work to estimate missing logs and reduce uncertainty across log, core, and well test permeability. We also experimented with other techniques, such as decision trees and linear regression. Their findings were contrasted with created and current empirical models.

Joshi et al.'s (2021) study examined the challenges and costs associated with using the conventional approach to well log evaluation. The authors developed a new method to forecast acoustic log in order to reduce the amount of time required to evaluate logs. They achieved this by recommending the use of neural networks and clustering to ascertain lithology, in addition to employing a supervised machine learning (ML) approach for regression. Since the foundation of these techniques is gamma-ray log values, a correlation is established between the two.

Wang and colleagues (2022) examined the difficulty of maintaining good maintained historical data. The authors of the article proposed a deep learning integrated neural network model with the self-attention mechanism for categorising and predicting long term sequence well log data. According to the authors, deep learning (DL) technology opens up new options for precise well log prediction that are unavailable. The authors claim that DL is a recently created artificial intelligence machine learning (ML) technique that builds a multilayer network to extract high-level features from input data. The authors claimed that two popular deep learning (DL) techniques for prospecting geophysical data processing and interpretation are recurrent neural networks (RNNs) and convolutional neural networks (CNNs). Additionally, although it has drawn a lot of attention for its usage in full-waveform inversion, dispersion curve choosing, and seismic data classification in geophysical exploration, the model has certain advantages such as shared convolution kernels and automatically generated features.

Zhu et al. (2022) looked into the problem of low accuracy when well logs are preserved using standard or traditional methods. The authors suggested a model for creating the missing logging curves of horizontal wells in shale gas reservoirs in an effort to meet the goal of retaining the accuracy of the well logs and to make it easier to explore and develop unconventional reservoirs.

The problem of missing, distorted, or destroyed well log data in older oilfields due to equipment failure, poor borehole conditions, shutdowns, and other causes was addressed by Wang et al. in their 2021 study. Well recording does, however, help geologists locate untapped natural gas, oil, and other resources, as the authors stated. Still, well log data are insufficient because they can only be obtained by drilling, which requires costly and time-consuming field trials. The authors developed the spatio-temporal neural network (STNN) algorithm to take use of the synergistic benefits of a long short-term memory network (LSTM) and a convolutional neural network (CNN).

Wang et al. addressed the problem of missing, distorted, or damaged well log data in older oilfields due to various variables such as equipment damage, poor borehole conditions, shutdowns, and other issues in their study from 2021. But as the authors pointed out, well recording helps geologists locate untapped oil, natural gas, and other resources. But well log data are always insufficient because they can only be obtained by drilling, which calls for costly and time-consuming field trials. The authors developed the spatio-temporal neural network (STNN) algorithm to take advantage of the combined advantages of a convolutional neural network (CNN) and a long short-term memory network (LSTM).

The issue of measuring well logs through the drilling process—which is always expensive and time-consuming—was examined by Shan et al. in 2021. In order to create hybrid neural networks for predicting missing well logs, the authors linked or merged convolutional neural networks (CNN), bidirectional long short-term memory (BiLSTM), and attention mechanisms. Additionally, alternative deep learning benchmark models, CNN, BiLSTM, and conventional machine learning models were created in order to compare with the models that were presented. The suggested strategy, according to the results, achieves improved prediction accuracy since it considers the spatiotemporal information found in well logs.

Well log missing was a problem that (Qiao et al. 2022) looked at. Strong nonlinear correlations between the well logs are necessary due to the complexity and variety of the reservoirs, according to the study's authors, who also noted that predicting missing well logs is an efficient approach to lower exploratory expenses. Attempting to tackle the issue, the authors suggested an approach that enhances the precision and stability of the missing well logs prediction, utilising a Bayesian optimised hybrid kernel extreme learning machine (BO-HKELM) algorithm.

Numerous studies have employed machine learning methods in one form or another to estimate missing well logs, such as gamma ray (GR), density logs (DEN), and acoustic logs (AC), from accessible well logs (Gowida et al., 2019: Gowida, 2020). (Fung et al. 1997) offer a plausible method for predicting logging curves for permeability and porosity based on well logs that are currently available by building a back propagation neural network (BPNN). Artificial neural networks (ANNs) hyperparameters were optimised for good logging reconstruction using a genetic approach, which was developed to improve prediction performance (Mo et al., 2015).

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 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) estimated the mechanical properties of rock formations using a random forest (RF) machine learning model. After being trained on data from several boreholes, the model was able to predict mechanical parameters with an accuracy of 89.6%. A convolutional neural network (CNN)-based deep learning technique was presented by Shi et al. in 2021 to assess the mechanical characteristics of rock using drilling data. For Young's modulus and Poisson's ratio, the suggested model produced mean absolute percentage errors (MAPE) of 5.12% and 5.92%, respectively. In order to anticipate the missing mechanical properties of rocks, (Han et al. 2020) created a hybrid model that combines an artificial neural network (ANN) with the k-nearest neighbour (KNN) technique. The model's prediction accuracy for the missing data was 86%. (Yang et al. 2019) presented a hybrid methodology to estimate the mechanical characteristics of rock from drilling data, based on a support vector machine (SVM) and a clustering method. The predictive accuracy of the model was 90.5% for Young's modulus and 93.3% for Poisson's ratio. In order to estimate missing rock mechanical parameters, (Li et al. 2020) suggested a hybrid model that combines principal component analysis (PCA) and a support vector machine (SVM). The model's prediction accuracy for missing data was 92.1%.

Zheng et al. (2021) investigated the deficiency of well-logging data, which can only be measured by expensive and time-consuming field testing. In an effort to provide a practical solution for the well log prediction that took into account the spatiotemporal features of the well log data, the authors employed a machine learning technique. Additionally, a convolutional neural network (CNN), long short-term memory (LSTM) neural network, and particle swarm optimisation were combined to extract the spatial and temporal features of well-logging data. The PSO technique was used to find the hyperparameters of the optimal CNN-LSTM architecture in order to predict logging curves in this study.

The challenge of forecasting missing logs due to equipment failure was examined by (Zheng et al. 2020). Without having to pay a hefty relogging charge, the author proposed a deep learning-based technique that combines an LSTM and CNN. Before the depth series features are imputed to the LSTM, the experiment employs the CNN layer to extract them at the beginning point, which improves the LSTM's feature memory and extraction capabilities.

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).

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).

- **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 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.
- **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.
- **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.
- **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.
- **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.
- **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.

- **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.

CONCLUSION

These days, ML and DL are highly valued in data science. In the last ten years, DL models—which combine sophisticated modelling techniques and reliable data management—have become increasingly popular for autonomous text analysis and disambiguation. The use of DL to complex modelling methodologies, trustworthy data management, and interpretation analysis in the ML/DL study arena ignites intense research interest. In the years to come, DL-based modelling may have significant effects once the myths surrounding it are disproved.

This article aims to provide a comprehensive overview of neural networks, including the evolution of NN into convolutional networks, which then became DBNs, and the development of DL models from conventional networks. Additionally, data regarding its much deep learning architecture—such as CNN, DBN, RNN, and LSTM networks—has been provided. By providing a comprehensive analysis of important DL tasks including the successful application of DL models such as DBN, CNN, and RNN, the researchers have ultimately set new benchmarks for cutting-edge results in ML/DL domains such as oil exploration, appraisal, drilling, and production. Although the study's earliest results are derived from particular ANN subfields, the performance of DL models seems promising. The main goal of this study was to examine several challenging issues concerning the estimation of missing well log data in oil exploration and several ML/DL models, including CNNS, DBN, RNN, GRU, and LSTM networks, that are employed for subsurface characterisation tasks.

The paper's analysis of the various models led to the following conclusions: (a) Even with the application of conventional ANNs' advanced capabilities to predict/estimate well log performance, ANN models—which are trained on enormous volumes of numerical data through statistical learning techniques—remain severely hindered by issues like slow convergence speed, poor local minima, and poor generalisation performance. (b) To begin with, data quality is important since deep learning models rely on the quality of the data used to train them for accuracy and reliability. DL models can detect and magnify issues with noisy, inaccurate, incomplete, inconsistently formatted, and other types of data since they look for patterns in the data. or skewed information. In order to minimise errors and guarantee that the data accurately captures the real-world phenomena that the models are intended to comprehend, dependable management and use of high-quality data are essential during the training phase of deep learning models. Second, data diversity is essential because robust representations that adapt effectively to new data are built by deep learning models only after they are exposed to a large variety of examples and variations. The models may not be able to handle novel and unseen inputs if the training data is overly limited or narrow in scope, which would result in poor generality and implementation. A DL model can discover a wide range of patterns and correlations by integrating a variety of data sources. enhancing its capacity to adjust to different situations and environments. Much more high-quality and diverse data is needed for deep learning models. Data management strategies, quality assurance procedures, and strong data integration strategies are required for these models. To minimise data-related issues and generate accurate and dependable model performance, data standards, enhanced data collection methods, and data validation protocols must be implemented. Multiple lines of evidence, expert knowledge, and mechanisms for quantifying uncertainty must all be included in the interpretation workflow to overcome the subjective character of geological and petro physical interpretation of missing well logs.

In conclusion, subsurface characterisation and reservoir models require the challenging but essential problem of estimating missing well logs. To get above these challenges, an interdisciplinary approach with rigorous interpretation methodology, robust data management protocols, and advanced modelling techniques is required. Research can address the technological, data-related, and interpretive challenges to improve the accuracy, reliability, and use of approximated well logs. Maintaining the current level of technological development, integrating data, and collaborating on research projects would increase the ability to precisely define subsurface reservoirs and support the creation of sustainable energy sources.

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