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# Enhancing facies classification in geological studies through artificial neural networks: A review

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A B S T R A C T

Geological studies rely heavily on facies classification since it offers vital information for reservoir characterization and hydrocarbon exploitation. Because facies are inherently complex and heterogeneous, traditional approaches frequently struggle to categorize them effectively. Artificial Neural Networks (ANNs) have shown great promise in recent years for improving the efficiency and accuracy of facies classification. This review assesses ANN applications for facies classification in geological investigations critically and it begins by delineating the essential principles of facies classification and the constraints of traditional methodologies. Then ANNs' theoretical underpinnings and applicability to tasks involving the classification of facies was explored. The different architectures and configurations of ANNs used in geological research were also examined, as well as the benefits and difficulties of their use. The several ANNs architectures and configurations used in geological research are examined, as well as the benefits and difficulties of putting them into practice. In order to enhance the efficacy of ANNs in facies classification, the paper also addresses the integration of auxiliary data sources, such as well logs, seismic, and core data. Furthermore, the application of new developments in Deep Learning methods, including Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), to facies classification were discussed. To guarantee solid and trustworthy classification results, factors including feature selection, data preparation, and model assessment metrics were also taken into account. Lastly, the review highlights possible avenues for future research and breakthroughs in leveraging ANNs for enhanced facies classification, precision and effectiveness in geological studies.

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## 1. Introduction

According to (Reading, 1996), "Facies" is defined as a volume of rock having specific characteristics. These characteristics might include any apparent property of rocks, such as their overall composition, appearance, or formation state, as well as any fluctuations in those qualities within a particular region. Facies constitute a continuous structure that may be grouped or separated in a lot of ways. They were classified according to rock type (siliciclastic or carbonate) and texture (Folk, 1954; Dunham, 1962); grain size for siliciclastic; Dunham, 1962; classification for carbonates).

In several definitions, the term "facies" has been expanded to include a specific depositional process or habitat, a well-sorted, fossiliferous, medium-grain quartz sand, for instance, is a simply descriptive lithofacies, while a medium-grained quartz dune sand might be a matching genetic description. The previous, merely descriptive definition of facies was preferred by some, who objected to the genetic concept (Middleton, 1978; Walker, 1984; Selley, 1985, 2000) and numerous others evaluated the idea of sedimentary facies. An interpretive (genetic) facies, according to (Anderton, 1985), is a term that summarizes how a particular unit of rock's deposition processes and environment are understood.

Interpretive or genetic descriptions of facies features are frequently employed. According to (Anderton, 1985), there shouldn't be any issues with the usage of interpretative facies as long as the context makes it evident which facies are descriptive and which are interpretative. Whether the term "facies" is being used in a descriptive or interpretive sense can usually be determined by looking at the context (Walker, 2006). There are several scales on which to define facies, including: the study's goal; amount of time available for measurements; and the quantity of descriptive features in the strata under examination (Walker, 2006).

**Facies Analysis:** The primary benefit of facies analysis is that, globally, only a few numbers of facies are found repeatedly in rocks of varying ages (Selley, 1985). If each rock bed was regarded as a separate entity, there would certainly be no significant order in the study of sedimentary rock. Facies features, however, are not very valuable when considered alone. A grasp of the context and associations of facies is important for environmental interpretations (Reading, 1986b) and, in turn, appreciating the predictive value of facies analysis.

**Facies Model:** Based on investigations of both recent sediments and ancient rock, a facies model, also known as a type model, in an idealized sequence of facies that provides a basic overview of a particular sedimentary environment (Walker, 1984). An idealized environmental summary or facies sequence is created by distilling the information that is currently available about a depositional environment in order to extract general information. A facies model should provide as more than just an overview of the surroundings, it should also provide the following

- A standard for comparative purposes.
- A framework and manual for upcoming observations.
- A predictor in novel geological contexts
- A comprehensive basis for understanding of the environment of the system that it represents (Walker, 1984).

A sedimentologists' most effective and influential instrument for categorizing and understanding archaic sediments is the facies model paradigm. The core components of every facies model differ greatly. Some models, like the delta facies models of (Coleman and Wright, 1975; Galloway, 1975), are founded on surface geomorphological assessments, while others—like the turbidite model of (Bouma, 1982) and the hummocky cross-stratification model of (Dott and Bourgeois, 1982)—aim to capture a whole depositional environment. The models of the fluvial facies belong to the latter group.

**Facies Sequence:** Facies whose interactions and transitions are important in the aspect of the depositional environment are known as facies sequences (Walker, 1984; Reading, 1986b). Therefore, it could be more appropriate to speak to "facies successions" instead of "facies sequences". Nonetheless, the original terminology is kept in order to maintain consistency with the historical literature. One important thing to keep in mind is that, even though single facies may possibly not provide much context for the depositional environment, the order in which they occur might provide for more information. The review "Enhancing Facies Classification in Geological Studies through Artificial Neural Networks" stems from the increasing recognition of the significance of facies classification in geological studies, particularly in fields like reservoir characterization and subsurface modeling. Facies classification involves identifying and categorizing different rock or sediment types based on various geological attributes. Traditional methods of facies classification may have limitations, and researchers or professionals in the field may be seeking more advanced and effective approaches to address challenges and limitations in traditional facies classification methods in geological studies. By exploring the application of Artificial Neural Networks, the goal is to enhance the accuracy, efficiency and overall effectiveness of facies classification processes in the context of complex geological formations.

The objectives of the Review are as follows as it aims to address several important challenges in geological studies related to facies classification.

- **Improved Accuracy and Efficiency:** By leveraging artificial neural networks (ANNs), researchers can achieve higher accuracy and efficiency in facies classification compared to traditional methods. ANNs have shown promise in capturing complex patterns and relationships in geological data, leading to more precise classification outcomes (Fakhari et al., 2020).
- **Handling Complexity and Heterogeneity:** Geological formations often exhibit complex and heterogeneous facies distributions, posing challenges for accurate classification. ANNs

offer the ability to model nonlinear relationships and capture subtle variations in geological features, thus enabling more effective classification of complex facies types (Tahmasebi et al., 2018).

- **Integration of Multisource Data:** The integration of multiple data sources, such as well logs, seismic data, and core samples, is essential for comprehensive facies classification. ANNs provide a framework for integrating diverse datasets and extracting meaningful patterns, resulting in more holistic and reliable classification results (Sun et al., 2021).

- **Robustness to Uncertainty:** Geological data inherently contain uncertainties, which can impact the reliability of facies classification outcomes. ANNs offer robustness to uncertainty by learning from noisy and incomplete data, thus providing more robust and reliable classification results compared to traditional statistical methods (Yuan et al., 2018).

- **Advancements in Geological Exploration and Reservoir Management:** By enhancing facies classification accuracy and efficiency, ANNs contribute to advancements in geological exploration and reservoir management. Accurate characterization of facies distributions within reservoirs is crucial for optimizing exploration and production strategies, leading to improved reservoir management and hydrocarbon recovery (Huang et al., 2021).

## 2. Material and Methods

### *2.1. Brief overview of traditional facies classification methods*

Sedimentary bodies are mapped and classified using sedimentary facies analysis; each sedimentary body developed under a different set of depositional conditions. Usually, facies are ascribed according to their paleontological or physical traits (Middleton, 1978; Dalrymple, 2010). Hydraulic and mechanical qualities, nevertheless, can be significantly impacted by the inherent textures and rock characteristics of different facies (Chang et al., 2000, 2002; Burton and Wood, 2013; La Croix et al., 2013, 2017; Baniak et al., 2014; He et al., 2016). According to Borer and Harris (1991), Dill et al. (2005), Khalifa (2005), Qi and Carr (2006), Qing and Nimegeers (2008), and other sources, the recognition of sedimentary facies is dependent on qualitative as well as quantitative parameters, such as mineral composition, texture and fabric, stratification, sedimentary structures, bioturbation, and grain-size dissemination. These variables can be employed in outcrop or core situations. But geological datasets are either scarce (like outcrop) or expensive (like core), therefore it might be difficult to build facies correlations with a regional perspective when there's not enough of control data. Because well log data represent the most plentiful and widely used dataset in subsurface investigations, facies distributions based on well log data are therefore greatly sought after (Berteig et al., 1985; Li and Anderson-Sprecher, 2006; Dubois et al., 2007) since they comprise the most comprehensive and plentiful dataset in subsurface research. Facies mapping may be possible by the prediction of facies using traditional wireline logs, which might expand findings from the core size (centimeters to meters) to the well scale (meters or tens of meters), and finally to the regional scale (> kilometers). However, the method of quantitatively identifying facies from well logs is currently being improved so that it may be used in deposits from various depositional settings in addition to a range of sedimentary basins (Tang et al., 2011; Wang and Timothy, 2013). Generally speaking, facies are determined by examining core samples. It is improbable that cores will be accessible during the whole subsurface interval of interest, nevertheless. As a result, centered on the facies characterization acquired using core samples and the number of measured well logs, mathematical techniques are often used to build a facies profile at the well location. In order to assign each sample to a distinct facies and cluster the samples measured by well logs in the specified number of facies, deterministic or probabilistic approaches can be used. Cut-off-based techniques and other straightforward deterministic methods may be utilized, although they are only suitable for a few numbers of samples. Considering statistical tools can explain several variables and the relationships between various qualities, they are typically selected (Doyen, 2007). The fact that statistical approaches quantify classification uncertainty is another benefit of using them. Stated otherwise, the likelihood of a sample exhibiting intermediate traits shared by two distinct facies is often comparable, and this represents the categorization uncertainty. Supervised and unsupervised classification techniques are used in statistical methods for facies categorization. Classifying facies throughout the well logs may be done by using supervised algorithms and assembling a training dataset if core samples are accessible. In situations when core samples are unavailable, meaning there isn't a training dataset, unsupervised methods can be utilized to optimize the differentiation between distinct features.

### *2.2. Overview of Facies in Geology and its Significance*

Facies in geology are significant for understanding the depositional environments and processes that shaped the sedimentary record. They provide information about the physical, biogenic, and chemical conditions during deposition (Dim, 2021). Facies analysis and classification are crucial for reservoir description and modeling, aiding in predicting the distribution of rock properties and the extent of reservoirs (Chicheng et al., 2017). The study of facies-potential coupling effects on reservoirs helps in analyzing the relationships between different sand bodies and their potential for hydrocarbon accumulation (Zhongliang, 2009). Time-specific facies (TSFs) are unique facies that characterize particular intervals of geologic time and provide insights into the interplay between processes of differing scales, such as alteration in redox conditions, sea level fluctuations, climate variations, and biotic evolution (Carlton et al., 2012). Additionally, facies analysis is important in metamorphic geology as it helps determine distinctive mineral assemblages that indicate specific metamorphic conditions (Martin and Hartwig, 2020). Facies in geology have several significant implications. Firstly, facies-potential coupling effects on reservoirs can provide details regarding the characteristics of oil and gas accumulation in different scales, such as sand body, sand layer, and core scales (Zhongliang, 2009). Secondly, facies analysis can help in understanding the conditions that shaped the environments of occurrence during deposition, as well as the different lithofacies associations and depositional cycles/successions (Dim, 2021). Thirdly, sedimentological analysis of facies can provide details of the source areas of sediments and the tectonic background of basins, helping in the understanding of basin evolution (Chen, 2014). Lastly, the study of facies can reveal the factors in charge of the creation of specific decorative grain fabrics, such as sedimentary tectonic background, ecology and biogliph, and diagenesis (Xu, 2001). Overall, facies analysis plays a vital part in comprehending the sedimentary processes, depositional environments, and geological history of an area.

### *2.3. Importance of facies classification in reservoir characterization*

In recent research, there has been an emphasis has been laid on the benefits of facies classification in reservoir characterization for understanding reservoir heterogeneity, optimizing production strategies, improving reservoir modeling accuracy, quantifying uncertainty, and enhancing exploration and development efforts. Below are some of the benefits of facies classification in reservoir characterization:

(a) **Understanding Reservoir Heterogeneity:** Facies classification helps in delineating different sedimentary facies within a reservoir, each with distinct properties such as porosity, permeability, and fluid saturation. Understanding this heterogeneity is essential for accurately characterizing reservoir architecture and predicting fluid flow behavior (Zhang et al., 2022).

(b) **Optimizing Well Placement and Production Strategies:** Accurate facies characterization enables better identification of high-quality reservoir zones, which is crucial for optimizing well placement and designing effective production strategies. By targeting areas with favorable facies characteristics, operators can maximize hydrocarbon recovery and minimize production risks (Chen et al., 2023).

(c) **Improving Reservoir Modeling and Simulation:** Facies classification provides the foundation for building realistic reservoir models. By integrating facies data into reservoir simulation workflows, forecasting models that take spatial variables into consideration can be produced by engineers. in lithology and fluid properties. This integration enhances the accuracy of reservoir performance predictions and supports decision-making processes (Li et al., 2022).

(d) **Quantifying Uncertainty and Risk:** Facies classification is essential for quantifying uncertainty and risk in reservoir characterization. By incorporating uncertainty assessments related to facies distribution and properties, practitioners can perform robust risk analysis and develop contingency plans to mitigate uncertainties associated with reservoir development and production (Wang et al., 2023).

(e) **Enhancing Exploration and Development Strategies:** Facies classification aids in the interpretation of depositional environments and geological processes that influenced reservoir formation. This knowledge is valuable for guiding exploration and development strategies, helping operators identify prospective areas for drilling and prioritize investment decisions (Smith et al., 2024).

## 3. Results and discussion

### *3.1. Basic Concepts of Artificial Neural Networks*

A technology for virtual intelligence called a neural network may conduct analysis and produce results by simulating the human brain. Because of the benefits of nonlinear classification and computation, its usage in reservoir engineering is progressively developing and has the potential to replace existing analytical methods for reservoir characterization. Unsupervised and supervised neural networks are the two different kinds of neural networks. Recently, neural network is a newly developed technology that is currently applied to many areas of log evaluation. The novel strategy has shown to be more effective than the traditional statistical approach (Goncalves, 1995; Wong, 1995). With a few exceptions, a numerous number of neural network applications that have been published are based on Back Propagation Neural Networks (BPNN) (Baldwin, 1992; Rogers, 1992; Goncalves, 1995; Wong, 1995 a, b; Fung, 1995) It made use of Learning Vector Quantization (LVQ), Self-Organizing Map, and Fuzzy ARTMAP. The input employed when BPNN is employed as a predictive model includes information from a variety of logging devices, including bulk density, resistivity, gamma ray, and neutron porosity. The BPNN produces outputs that correlate to many output characteristics, including permeability, porosity, and rock matrices. A set of input and output vectors are utilized to train the supervised Bayesian Neural Network (BPNN). The error back-propagation algorithm is the learning algorithm that is frequently utilized (Rumelhart, 1986). Despite the algorithm's success in numerous applications, its drawbacks, namely its lengthy training period, have made practical deployment difficult. This necessitates enhancing the fundamental BPNN algorithm or alternative network designs.

### *3.2. Artificial Neural Networks (ANNs) in Geological Applications*

Previous research has concentrated on applying statistical techniques, such as discriminant analysis, to analyze facies from well logs; (Sakurai and Melvin, 1988; Avseth et al., 2001; Tang et al., 2004), building large-scale, geologically plausible, static reservoir models requires highly precise sedimentary facies forecasting such as naïve Bayes classifier (Li and Anderson-Sprecher, 2006; He et al., 2016), fuzzy logic (Cuddy, 2000; Saggaf and Nebrija, 2003), and support vector machines (El-Sebakhy et al., 2010; Wang et al., 2014; Deng et al., 2017). Artificial Neural Networks (ANN) have also been fully applied in the last ten years (Derek et al., 1990; Wong et al., 1995; Siripitayananon et al., 2001; Bhatt and Helle, 2002; Wang and Timothy, 2012) due to its capacity to decipher non-linear correlations, quantify learning from training data, and collaborate with other forms of artificial intelligence in the prediction of sandstone and carbonate lithofacies (Bohling and Dubois, 2003; Kordon, 2010). The feedforward ANN classifier known as the Multilayer Perceptron Classifier (MLPC) is not a very good classifier for pattern recognition, its benefits show to a wide range of scientific and academic applications for it. When it comes to choosing sensitive input variables, designing learning methods, choosing network architecture, and customizing codes for unique problems, MLPC is incredibly adaptable (Wang and Carr, 2012 a, b). Because MLPC can solve complicated nonlinear problems stochastically, it is a valuable research tool, particularly in the use of shale lithium-ion batteries (Wang and Carr, 2012 a, b).

Although most prior approaches for determining facies from wireline logs have identified facies at each well data point, they have not taken vertical continuity in the facies profile into consideration. Every sample in the well log was identified apart from the ones next to it, consequently facies profiles produced in this manner, implausible facies successions tend to emerge. For a considerable amount of time, Markov Chain Analysis (MCA) has been utilized to ascertain if the underlying facies or the occurrence facies in a geologic succession are interdependent (Gingerich, 1969; Le Roux, 1994; Xu and MacCarthy, 1998; Bohling and Dubois, 2003). MCA data can be used as independent evidence to support interpretations of facies associations since they show the existence of favored vertical occurrences of facies in a sedimentary succession (Miall, 1973; Powers and Easterling, 1982; Wells, 1989; Carle, 1999). In complex and varied sedimentary systems, this enhances facies relationships and facies succession prediction (Weissmann, 2005).

### *3.3. Types of ANNs used in Facies Classification*

Different types of Artificial Neural Networks used in facies classification include Deep Neural Networks (DNN) such as DeepLabv3+ and Generative Adversarial Network (GAN) as shown in Figs 1 and 2 below respectively after (Kaur et al., 2023). 1D-CNN model (Soleimani et al., 2023) Recurrent Neural Network (RNN) models like Long Short-Term Memory (LSTM), bidirectional long short-term memory (Bi-LSTM), and Convolutional Recurrent Neural Network (CRNN) (Tian and Verma, 2022) and Deep Learning Neural Network with a 3D Conditional Random Field (CRF) layer (Ekaterina and Anton 2022). Additionally, a modified CNN that incorporates learnable Gabor convolutional kernels been utilized for facies classification (Wang and Alkhalifah, 2023).

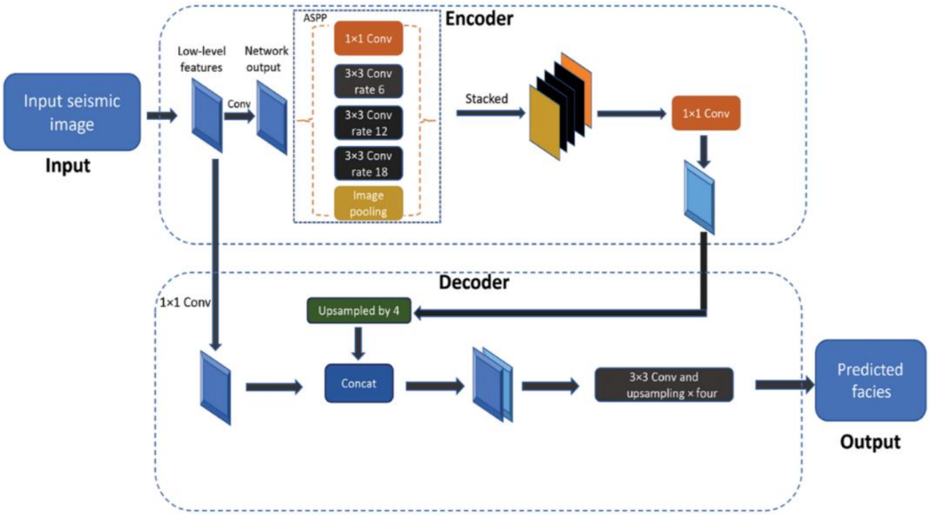


**Fig. 1.** DeepLab architecture for facies segmentation. Multiscale contextual information is encoded by the encoder using atrous convolutions at multiple scales and the segmentation results are refined along the object boundaries by the decoder module after (Kaur et al., 2023).

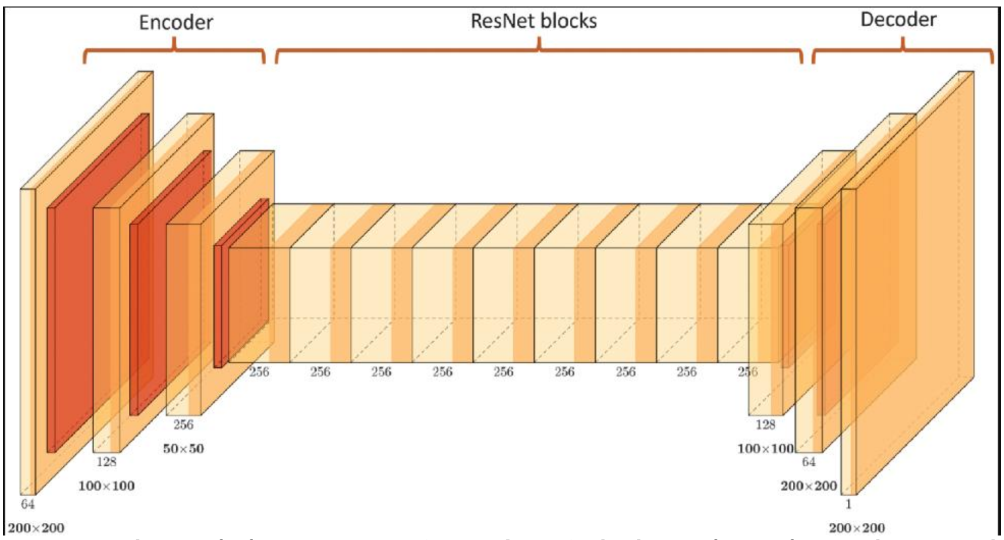


**Fig. 2.** GAN generator architecture for facies segmentation (Kaur et al., 2023). The objective function for network training in this case is a combination of adversarial loss and multiclass cross-entropy loss.

Other types of artificial neural networks that are been used for facies classification includes Convolutional Neural Network (CNN), which has shown high accuracy in seismic facies classification and seismic interpretation (Mohammed et al., 2023; Wang and Alkhalifah, 2023). Additionally, a multi-layer CNN are used for automatic recognition of seismic facies with special reflection structures, providing better accuracy and efficiency compared to manual interpretation (Wang and Alkhalifah, 2023). Another type is the Gabor-CNN, which combines the interpretability of Gabor filters with the learning ability of CNNs, resulting in improved generalization for facies classification tasks (Mohammed et al., 2023). The Deep Neural Network (DNN), are used for instant and consistent facies classification of carbonate rocks (Nan et al., 2023). Additionally, the use of a 1D-CNN model that has been recommended for geological facies classification in wells, displaying outcomes that are more precise than other models (Jiachun et al., 2023). Shallow ANN (SANN) is another type of Neural network that is frequently used in exceptionally nonlinear regression and classification applications, and it was inspired by biological neural networks. There is currently much coverage on the use of Shallow Artificial Neural Networks (SANN) in facies/lithology prediction (Wang and Carr 2012; Ma, 2011; Tang et al., 2011). Comparisons, however, reveal that for facies classification, shallow ANN offers no appreciable advantage over more established machine learning techniques like Support Vector Machines (SVM) and Random Forests (RF) (Deng et al., 2019; Cracknell and Reading 2014; Halotel et al., 2019). The computational efficiency of the shallow ANN is compared to that of other neural network architectures, and it is considered as the essential component for Deep Neural Network structures. Three layers make up a shallow ANN, also known as a multilayer perceptron (MLP): an input layer, a hidden layer, and an output layer as shown in Fig. 3. These different types of neural networks offer various advantages and can be suitable for different types of facies classification tasks.

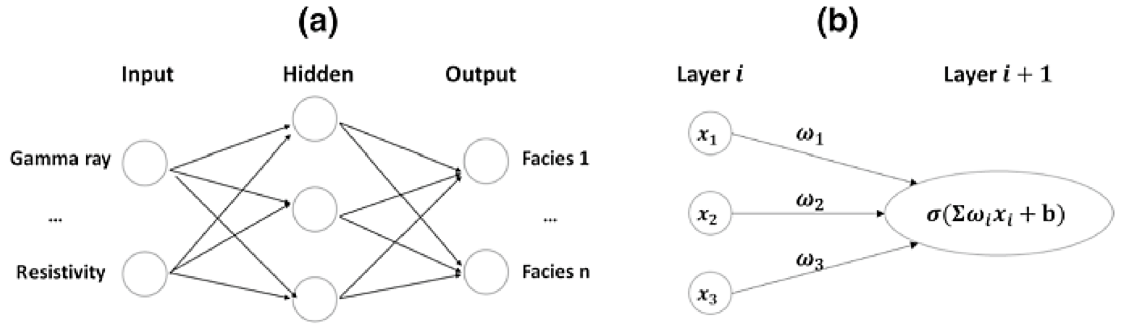


**Fig. 3.** The shallow neural networks (MLP) design. Panel (a) displays the panel and the fully connected input, hidden, and output layers (b) demonstrates the relationship between two neurons in nearby layers after (Tiang et al., 2021).

### *3.4. Review on the Advantages of Artificial Neural Network (ANN) in Geological Facies Classification*

Artificial neural networks (ANN) can be used in geological facies classification to improve accuracy and efficiency. ANN models, such as deep learning models, have been developed to classify rock facies based on various geological data, including well logs and seismic attributes. These models can learn the lithological characteristics of rocks and classify facies based on their physical and chemical properties (Mohammad et al., 2023). ANN models have been trained on different optimization algorithms and have illustrated more accuracy compared to alternative classification techniques like support vector machines and nearest neighbor models (Nan et al., 2023). Additionally, explainable deep learning methods have been explored to provide interpretability and retain human intervention in the classification process (Ekaterina and Anton, 2022). These methods use prototype-based neural networks to explain the function of the seismic facies classifier and help with quality control (Jiachun et al., 2023). Overall, ANN models offer a powerful tool for geological facies classification, improving interpretation consistency and efficiency (Miao and Sumit, 2022). Deep learning models, such as Artificial Neural Networks (ANN), offer several advantages for geological facies classification. One advantage is the ability to process well log data, is assumed as the main advantage of the proposed 1D-CNN model (Mohammad et al., 2023). Another advantage is the ability to provide consistent and repeatable results, reducing the reliance on human interpreters' expertise and experience (Nan et al., 2023). Additionally, ANN models can capture long-term dependencies and spatio-temporal relationships in geological procedures, rendering them appropriate for analyzing gradual variations in lithofacies (Jiachun et al., 2023). ANN models also allow for the interpretation of the underlying basis, providing insights into the function of the facies classifier and aiding in the quality control process (Miao and Sumit, 2022). Overall, ANN models offer efficient and effective solutions for geological facies classification, improving accuracy and interpretability.

### *3.6. Advantages/Strength of ANN compared to traditional methods*

Artificial Neural Networks (ANNs) provide a number of advantages over rival's machine learning techniques. ANNs can draw fine distinctions, patterns, and hidden information from data without complex mathematical considerations (Вісник, 2023). They are effective in both classification and regression problems, providing enhanced functionality at a reduced processing expense (Mushfiqur and Asadujjaman, 2021). ANNs have excelled in various learning tasks, such as image processing and emotion analysis (Baraniya, 2023). They are not impacted by the input variables of the model and can recognize important correlations that are not visible (Sharon, 2023). Additionally, ANNs can be utilized for diagnosis and prediction in healthcare, enabling personalized treatments and improving outcomes and survival rates (Xiaoyu, 2021) Overall, ANNs offer the advantage of accuracy, efficiency, and the ability to uncover hidden patterns and correlations in data.

### *3.7. Limitations of ANNs compared to traditional methods*

Artificial Neural Networks (ANNs) have limitations in facies classification. One limitation is poor generalization with less data for training pairs, resulting in reduced accuracy (Wang and Alkhalifah, 2023). Another limitation is the reliance on human interpretation and expertise, leading to inconsistency and lack of repeatability (Mohammad et al., 2023). Additionally, ANNs require labeled data for supervised learning, which might be difficult to handle large seismic datasets and limited annotated samples (Nan et al., 2023). Furthermore, ANNs are often considered "black boxes" that lack transparency, making it difficult to understand how they classify seismic facies (Hanpeng et al., 2023). These limitations highlight the need for improved methods in facies classification that address issues of generalization, interpretation, data availability, and transparency.

### *3.8. Recent Case Studies, their study's purpose, methodology, and conclusions*

Real world case studies on the use of Artificial Neural Networks (ANN) in facies classifications (Table 1) have been undertaken in various geological settings. (Nan et al., 2023) developed an end-to-end deep neural network (DNN) for consistent facies classification of carbonate rocks from image logs, achieving 77% accuracy on a test set. (Shang et al., 2023) used a deep learning image-recognition algorithm to automatically recognize facies types from core images, achieving a recognition accuracy of 91.12%. Another study proposed a 1D-CNN model trained on well-log data for geological facies classification, outperforming support vector machine and nearest neighbor models (Mohammed et al., 2023). A deep neural network-based framework for seismic facies classification was proposed by incorporating uncertainty analysis and achieving accurate classification results (Harpreet et al., 2023). Lastly, Li and Anderson (2006) investigated the use of CNN models for seismic facies analysis and introduced the SHAP tool for visualizing the contribution of seismic attributes to classification results, demonstrating the effectiveness of their approach (Jiachun et al., 2023). But virtually few articles address the limitations of using Artificial Neural Network (ANN) and the requirements that must be met to ensure successful applications.

**Table 1.** Real world case studies on the use of Artificial Neural Networks (ANN) in facies

| Reference | Study aim | Approach | Findings |
|---|---|---|---|
| Santos et al., 2022 | The study aimed at the development of a computational system based on deep Recurrent Neural Networks (RNNs). | Deep learning neural network with a 3D conditional random field layer and Pseudo-labeling technique with predicted labels added to the training set | The proposed method for lithology identification outperforms other learning approaches. The Deep Recurrent Neural Network (RNN) approach is effective in identifying lithofacies patterns. |
| Ali et al., 2020 | The paper buttressed those seismic facies classification is important for reservoir characterization and evaluation. - Artificial Neural Networks were utilized to classify lithology in carbonate reservoirs. | Multilayer feed forward network (MLFN) - Probabilistic Neural Network (PNN) | PNN technique classified the carbonate reservoir into four facies. - MLFN technique classified the carbonate reservoir into two facies. |
| Ali et al., 2020 | The Paper focused on lithofacies classification and distribution in heterogeneous channelized systems using Neural network algorithm used to predict seismic facies in carbonate reservoirs | Supervised artificial neural natural (ANN) algorithms for seismic facies classification. - Probabilistic Neural Network (PNN) for predicting facies in carbonate channelized zone. | The study demonstrated the use of neural networks to predict seismic facies in a heterogeneous channelized reservoir. |
| Mingliang, et al., 2020 | The purpose of the paper was on seismic and lithologic facies mapping using neural networks. - It plays an important role in hydrocarbon exploration and reservoir characterization | Supervised convolutional neural network and semi-supervised generative adversarial neural network | Seismic facies classification using supervised convolutional neural networks and semi-supervised generative adversarial networks – Mapping of seismic and lithologic facies from 3D reflection seismic data. |
| Nan et al., 2023 | The paper proposes using a modified U-Net deep neural network (DNN) for instant and consistent facies classification of carbonate rocks from acoustic image logs and gamma ray logs. | The approach involved training an end-to-end deep neural network (DNN) for facies classification. The DNN is modified from the U-Net model for image segmentation. | The trained DNN achieves 77% classification accuracy for the test set. It also provides reasonable predictions for challenging unlabeled sets. |
| Yadigar et al., 2019 | The Paper aims to develop an effective deep learning model for geological facies classification. | A new 1D-CNN model trained on various optimization algorithms is proposed and is compared with other models like RNN, LSTM, SVM, and k-NN | The proposed 1D-CNN model shows more accurate results compared to other models. - The model is recommended as a suitable and effective approach for lithological discrimination. |
| Santos et al., 2022 | The deep recurrent neural network (RNN) approach is effective in identifying lithofacies patterns. | Deep recurrent neural networks (RNNs) with bidirectional long-short-term memory (BiLSTM) - XGBoost, Random Forest, Naïve Bayes, and support vector machine (SVM) learning approaches | Deep recurrent neural networks can effectively identify lithofacies patterns from well logs. - The proposed method outperforms other learning approaches for lithology identification. |
| Nan et al., 2022 | The article focused on reservoir training deep neural network for facies classification. | An end-to-end deep neural network (DNN) for facies classification was trained using acoustic image logs and gamma ray logs. | Deep neural network (DNN) can accurately identify facies of carbonate rocks from image logs. It provides more consistent and higher-resolution predictions compared to manual classification. |

*3.9. Future trends and Directions in the Use of Artificial Neural Network in Facies Classification*

Artificial neural networks (ANNs) are being increasingly used in facies classification. One future trend is the development of Deep Learning models based on ANNs, such as 1D-CNN and U-Net, that have had encouraging outcomes in accurately classifying lithological facies from well logs and image logs (Mohammed et al., 2023; Nan et al., 2023). Another direction is the incorporation of uncertainty analysis into the workflow using a Bayesian framework, which helps reduce the need for human intervention and individual biases in interpretation (Harpreet et al., 2023).

Additionally, learnable Gabor convolutional kernels in CNNs has been proposed to improve generalization for facies classification, particularly in seismic images with lower signal-to-noise ratios (Wang and Alkhalifah, 2023). These advancements in ANNs offer the potential for more efficient, consistent, and high-resolution predictions, contributing to automatic interpretation of facies from various types of logs (Nan et al., 2022). Other future trends and directions in the use of Artificial Neural Network (ANN) in facies classification includes:

**- Integration of Explainable AI (XAI):** There is a growing need for interpretable and explainable AI models in various domains, including geosciences. Future research may focus on developing ANNs with enhanced interpretability to provide clearer insights into the decision-making process, making them more trustworthy for geoscientific applications (Lipton, 2016).

**- Transfer Learning and Pre-trained Models:** Researchers may explore the effectiveness of transfer learning and pre-trained neural network models for facies classification tasks. Leveraging knowledge from models trained on large datasets may enhance the execution of ANNs when labeled data in the geoscience's domain is limited (Pan and Yang, 2010).

**- Hybrid Models and Ensemble Approaches:** Future research might focus on combining ANNs combined alongside additional machine learning methods or ensemble methods to enhance overall model performance. Hybrid models that integrate the strengths of different algorithms could provide more robust solutions for facies classification (Polikar, 2012).

**- Incorporation of Multi-source Data:** Future directions may involve exploring the integration of diverse data sources, such as well logs, seismic data, and core samples, into ANN models. Creating models that can manage and assemble information from multiple sources efficiently can lead to more comprehensive and accurate facies classification (Al-Rfou, 2016).

**- Uncertainty Quantification:** Addressing uncertainty in predictions is crucial for geological applications. Future research may focus on developing ANNs that can provide uncertainty estimates, aiding geoscientists in establishing better judgments based on the model's dependability predictions (Gal and Ghahramani, 2016).

### *3.10. Environmental and ethical considerations in geological studies using ANNs*

Artificial Intelligence (AI) methods are being employed more frequently in Earth Sciences to gather important data from large amounts of data. However, it is important to consider environmental and ethical considerations in geological studies using Artificial Neural Networks (ANNs). The use of ANNs can help eliminate data inhomogeneity and potential errors, enabling the determination of the order of influence of chemical elements on health indicators and the definition of limit values for the influential elements. ANNs are an appropriate method for analyzing environmental and health data in medical geochemistry (Dias and Dalton, 2022). Additionally, best practices and moving beyond off-the-shelf approaches are necessary when deriving scientific insights from AI methods (Dias and Dalton, 2022). It is crucial to ensure that research funding and training choices in the Earth and environmental sciences equip the next generation of geoscientists with the capacity to leverage advances in AI while considering sustainability, ethics, and trustworthiness (Fajcikova, 2017).

### *3.11. Research gaps and opportunities for future progress in the field of ANN*

The most promising research directions in the area of artificial neural networks include optimization techniques, feature extraction and selection, clustering, and the growth of more efficient and accurate systems. Research directions have been identified through the analysis of various articles and keywords (Kariri, 2023). Additionally, the utilization of artificial neural networks in online social network and virtual community research has shown promise in determining emotional meaning, classifying messages, and making recommendations (Walczak, 2022). Furthermore, advancements in deep learning, explainable AI, transfer learning, and human-AI collaboration are expected to drive future research in intelligent systems and AI techniques (Ismail, 2022). In the specific context of artificial neural networks, addressing the problems of local minimal, instability, and limited maximum accuracy can result in enhanced efficiency (Harpreet et al., 2023). Finally, in the field of data communication networks, there is a need to overcome challenges associated with the analysis of networking data through AI/ML, enabling the adoption of AI/ML for networking (Jiachuan et al., 2023).

**Summary:** This review examines the use of Artificial Neural Networks (ANNs) to improve facies classification in geological studies. It discusses the limitations of traditional methods, highlights the advantages of ANNs, explores methodological approaches, emphasizes the integration of multisource data, presents case studies, and discusses future directions and challenges. Overall, the review underscores the potential of ANNs to enhance facies classification accuracy and efficiency in geological studies.

## 4. Conclusion

In conclusion, "Enhancing Facies Classification in Geological Studies through Artificial Neural Networks" A review, underscores the significant strides made in leveraging advanced computational methods to unravel the complexities of geological formations. Artificial Neural Networks (ANNs) have emerged as powerful tools in the realm of facies classification, offering unprecedented capabilities to decipher intricate patterns within diverse datasets. The application of ANNs in geological studies has demonstrated promising results, enabling more accurate and efficient classification of subsurface formations. The inherent capacity of Artificial Neural Network (ANN) to learn intricate relationships and nuances within geological data has contributed to a paradigm shift in how geoscientists interpret and understand facies variations. The journey into enhancing facies classification through ANNs has not only improved the speed and precision of geological analyses nevertheless it has additionally provided opportunities for interdisciplinary collaboration. As these networks continue to evolve, incorporating advancements such as explainable AI and ensemble methods, the reliability and interpretability of facies predictions are likely to further enhance. However, challenges persist, including the need for extensive and high-quality labeled datasets and the ongoing quest for model interpretability. Overcoming these challenges will be pivotal for the continued success and widespread adoption of ANNs in geological studies. In essence, the pursuit of enhancing facies classification through Artificial Neural Networks is an ongoing and dynamic exploration. As researchers delve deeper into optimizing architectures, refining training methodologies, and addressing interpretability concerns, the fusion of geology and artificial intelligence promises to unlock unprecedented insights into earth's subsurface dynamics, ultimately advancing our understanding of geological phenomena.

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