Journal Homepage: http://ijcpe.uobaghdad.edu.iq
Iraqi Journal of Chemical and Petroleum Engineering
Vol. 25 No. 3 (September 2024) 43 – 49
EISSN: 2618-0707, PISSN: 1997-4884

Pattern recognition approach (PRA) for identifying oil reservoir lithology of Camaal oil field, Yemen

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Abstract

The accurate determination of reservoir lithology remains a challenge in petroleum engineering. There are some conventional techniques available to determine the lithology. However, the application of those techniques has been long and complex. So, the main goal of this study is to simplify the identification of reservoir lithology. This paper presents a Pattern Recognition Approach (PRA) to identify the reservoir lithology simply and accurately. It is type of artificial neural network. Four wells from the Camaal Field were chosen to develop this approach. Around 32400 data points from the previous wells were digitized. The PRA approach used depth, gamma ray, lithology, sonic, neutron, and density logs as inputs. The model classifies lithology into permeable and impermeable rocks, further categorizing them into clastic and carbonate rocks, and subsequently into specific types into sand, sandstone, dolomite and limestone. The results show that the proposed approach provides a suitable prediction of lithology with higher accuracy compared with actual lithology. The model demonstrates high accuracy rates in identifying various lithologies, with overall accuracies of 76.2% for permeable/impermeable rocks, 94.9 for clastic/carbonate rocks, 86.2% for sand/sandstone, and 92.8% for dolomite/limestone.

Keywords: Artificial neural network; reservoir lithology; artificial model; rock types; lithology identification.

Received on 17/04/2024, Received in Revised Form on 08/06/2024, Accepted on 08/06/2024, Published on 30/09/2024

https://doi.org/10.31699/IJCPE.2024.3.5

1- Introduction

In the exploration and production of petroleum, lithology must be determined from well-log data. The quantitative examination of logging data can be used to build the lithology model of a reservoir. The amount of logging data is constrained due to the high expense of drilling cores. The distributions of logging data from various lithologies overlap as a result of the complexity of lithology, which broadens the range of identification options. Therefore, it is necessary to employ techniques that offer precise ways to make lithology forecasts. Identification of formation lithology essentially depends namely on neutron, density, and sonic porosities as well as formation radioactivity. The physical properties of sediments like natural radioactivity, resistivity, density, compressional/ shear sonic travel time, and neutron porosity commonly measured through geophysical logging, are used for identification of the lithology of hydrocarbon-bearing reservoirs. A quick look or cross-plotting technique will be tedious and time-consuming for identifying lithology using conventional well log responses [1, 2].

The Camaal area is located in the Hadramout region in east central Yemen. Camaal area is considered one of the most important oil provinces in Yemen, which include a great number of oil wells. The Qishn Formation was deposited as predominantly was post-rift sediments in the east-west oriented Say'un–al Masila rift basin that initiated during Late Jurassic to Early Cretaceous as part of the second Mesozoic rift phase. Deposition was related to a regional east to west transgression overlying a regional lower Cretaceous unconformity at the top of the Sa'af Member.

2- Artificial neural networks

Many artificial intelligent systems are used in the petroleum engineering area [3, 4]. Estimation of lithology from well logs in heterogeneous formation is difficult to solve by the quick look interpretation method [5-7]. However, many artificial neural network (ANN) tools have been successfully utilized for the determination of lithology using the transformation between well logs [8-11].

In recent years, lithology has been extensively identified using artificial intelligence based on well logs, and much research has been done in this area. The first determined lithology from well logs using a back-propagation artificial neural network was done by Rogers [21]. The artificial neural networks model proposed to predict lithology using two wells in the Klotar oil field [12-14].

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The artificial neural networks model was also presented to identify the kind of lithology of a layer as it was being drilled using neighbor well data and real-time drilling data from 12 wells in the South Pars gas field in southern Iran [15-19].

3- Machine learning techniques

A novel machine learning-based methodology was introduced for incorporating seismic and well-log data to determine the lithology using thin-section photos in a deep marine clastic setting offshore West Africa [20-22]. In addition, a conventional single classification algorithm such as decision trees, Support Vector Machines, and Bayes was developed to determine the lithology of the Longqian region of China using three wells in the daan section [8, 23]. The coal pay zones were also predicted using a variety of machine learning algorithms using six wells in the Surat Basin of Australia [24-26]. The supervised learning algorithms, the unsupervised learning algorithms, and the machine learning algorithm were proposed in order to categorize and predict the geological facies using well-log data in the Anadarko Basin, Kansas [26, 27]. Moreover, a fuzzy artificial intelligence was presented to detect lithologies using wireline logs and core data from a specific drill in the Campo de Namorado [27]. The machine learning techniques were developed to forecast the lithology for surface drilling data and lithology information from core samples obtained during previous scientific drilling operations. The generative adversarial networks were used to recreate thin-section images and identify carbonate lithology. The Extreme Gradient Boosting and Bayesian Optimization classifier and the three machine learning algorithms were proposed for identifying the lithology of Daniudui and Hangjinqi gas fields and the lithology while drilling respectively [23, 24, 27]. A coarse-to-fine architecture that incorporates outlier detection, multi-class classification, and a tree-based classifier was suggested to identify the lithology using two actual well-logging data sets. An artificial neural network and hidden Markov models (ANN-HMM) hybrid framework was proposed to classify the lithological sequence. A novel and effective RST-based granular computing approach was suggested using well-log features to categorize the ten lithology classes [11, 26, 27]. A deep learning-based technique was proposed for mineral identification to integrate image and hardness minerals [26, 27] and a method for automatically classifying carbonate thin sections derived from plane-polarized and cross-polarized microscope images similar to natural rocks found in the Brazilian pre-salt reservoir. In addition, a set of techniques and processes proposed for the identification of complicated lithologies from log data in the Permian Longtan Formation by analyzing the log response characteristics of various lithologies based on conventional log curves, and a cross-domain lithology detection approach was presented to integrate the geological data and domain adaption. Machine learning techniques were developed for the characterization of lithfacies properties of Yemeni carbonate reservoir rocks [28, 29].

From the previous studies, using of artificial intelligence models and machine learning techniques to identify the lithology will be increased regarding their achievements in this area and their accuracy comparing with conventional methods.

Therefore, the aim of this study is to develop the Pattern Recognition Approach for the identification of the lithology of Camaal oil fields simply and accurately. So, the following objectives are proposed as follow:

- First, the PRA approach used all data to classify the lithology into permeable and unpermeable (Shale) rocks.
- Next, the PRA approach used the previous permeable rocks data to categorize the lithology into clastic and carbonate rocks.
- Then, the clastic data is classified into sand and sandstone.
- Finally, the carbonate data is categorized into dolomate and limastone rocks.

In addition, the accuracy of this model is obtained by comparing the predicted lithology data with actual data. It is expected that the proposed approach will be helpful in improving the accuracy of lithology identification in less time.

4- Methodology

4.1. Data description

Around of 32400 data points were collected from four wells of Camaal oil fields in Yemen. 9440 data points are from well A, 10000 data points from well B, 2000 data points from well C, and 10950 data points from well D. These data were generated by digitizing their logs by Neuralog program. The digitized data are depth, gamma ray, lithology, density, neutron, and sonic porosities. To ensure data integrity, the collected samples underwent thorough pre-processing steps. These steps involved checking for data consistency, identifying, and removing duplicate entries, and addressing any missing values. This meticulous data preparation process was crucial for minimizing uncertainties in subsequent computations.The main lithologies of these wells are shale, sand, sandstone, dolomite, and limestone. In this study, 70%, 15%, and 15% of the studied data were used for training, validating, and testing respectively. Table 1 describes the total data points with their different ranges.

Table 1. Shows the Ranges of the Total Data Points

	Min	Max
Gamma Ray, api	7.87	146.91
Density Logs, g/cc	1.93	2.95
Neuron Logs, v/v	-0.01	0.45
Sonic Logs, us/ft	2.87	141.76
Depth, ft	520	6179

4.2. Pattern recognition approach (PRA)

Pattern Recognition Tool is a type of Artificial Neural Network. It used to classify input data regarding how they are come together in the input space. The Pattern

Recognition Tool in networks is one of the most attractive topics in the ANN field.

Before using the Pattern Recognition method, the first step is to define the problem by selecting a data set.
The pattern recognition problem is defined by arranging a set of input vectors as columns in a matrix and another set of target vectors for indicating the classes to which the input vectors are assigned. The target data has only two classes; each scalar target value is set to either 1 or 0, indicating which class the corresponding input belongs to. Tangent sigmoid output functions (tansig) as shown in Fig. 1 are often used for the pattern recognition approach.

The standard network that is used for pattern recognition is a two-layer. The function pattern net is a specialized version of the feedforward network, except that it uses the hyperbolic tangent sigmoid transfer function (tansig) in the last layer and the feedforward network, with sigmoid transfer functions in both the hidden layer and the output layer. The hidden layer and number of input/output are shown in Fig. 2. These hidden layers and a number of neurons might want to come back and increase this number if the network does not perform as well as its expectation. The number of output neurons is equal to the number of elements in the target vector (the number of categories).

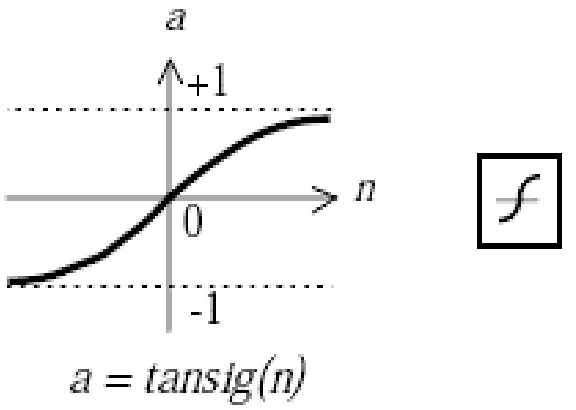

Fig. 1. Tan-Sigmoid Transfer Function

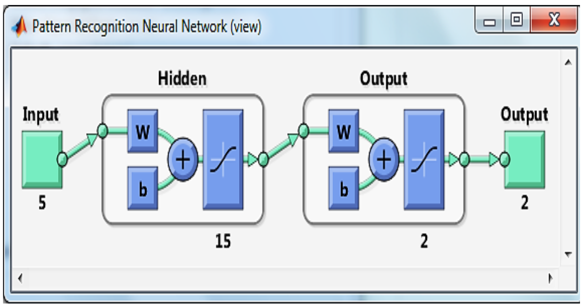

Fig. 2. Depicts the Structure of Neural Network

In this study, Fig. 3 shows the expert procedure of the proposed approach as follows:

1. First, all data used to classify the lithology according to permeable and unpermeable (Shale) rocks.
2. Next, the previous permeable rocks data was used to categorize the lithology into clastic rocks and carbonate rocks.
3. Then, the clastic data is utilized to classify the lithology into sand and sandstone.
4. Finally, the carbonate data is used to recognize the lithology of dolomate from limastone rocks.

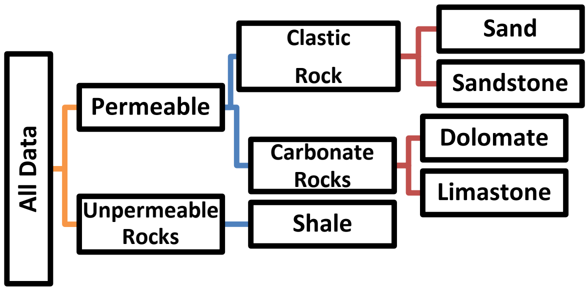

Fig. 3. Shows the Expert Procedure of Pattern Recognition Approach

In the traditional well logs interpretation, lithology classification is usually performed by experts with relevant professional knowledge, which greatly limits the development of the industry whereas the proposed model has the ability to identify lithology with their own expert.

5- Results and discussions

In this study, the Pattern Recognition Approach is applied four times as shown in Fig. 3. In the First step, the proposed approach used all data to identify the lithology of permeable and unpermeable (Shale) rocks. The confusion matrices are shown in Fig. 4 for training, testing, and validation and the three kinds of data combined. The network outputs are very precise, as you can see by the high numbers of correct responses in the green squares and the low numbers of incorrect responses in the red squares. The lower right blue squares illustrate the overall accuracy of about 76.2%. Fig. 5 shows the first error histogram.

Secondly, the approach used only permeable rocks to identify the lithology of clastic rocks (sand and sandstone) from carbonate rocks. Fig. 6 illustrates confusion matrices with an overall accuracy of about 95%. Fig. 7 shows also their error histogram.

Thirdly, the Pattern Recognition Tool applied the clastic data to categorize the lithology of sand and sandstone. Fig. 8 shows confusion matrices with an overall accuracy of about 86.2%. Fig. 9 shows also their error histogram.
Finally, the Pattern Recognition approach used carbonate data to identify the lithology of dolomate and limastone rocks. Fig. 10 shows confusion matrices with an overall accuracy of about 93%. Fig. 11 shows also their error histogram.

Table 2 summarizes the accuracy of the PRA approach to identify Camaal oil field lithology. This shows the PRA model achieved accepted results with classified permeable and nonpermeable rocks and the best with other classifications.

Moreover, the overall accuracy of proposed model is compared with published machine learning model (Al-khudafi, 2023). The comparison show the pattern recognition approach performs well for prediction the lithology of Camaal oil field as shown in Table 3. In additional, the use of a large dataset (32000 data points) strengthens the validity of the proposed approach model's predictions and showcases its robustness.

In this study, we employed the largest databases to develop this model. Our results demonstrate that the developed model achieved superior accuracy compared to published machine learning model for predicting the lithology as shown in Table 3. Additionally, Table 2 and Table 3 illustrate a respectable balance between the training and testing APRE (%) values of this model. Furthermore, Table 3 also highlights the superior performance of the proposed technique in predicting the lithology, showcasing the highest accuracy.

Table 3 also show the PRA model perfectly predicting the different patterens with the lowest average absolute present relative erroir (AAPRE). Finaly, we can noticed that the PRA model used a large data comparing the other published study and predicting lithology with wide range and does not take long time comparing with the other conventional methods.

Fig. 4. Displays the Confusion Matrices of Permeable /Unpermeable (Shale) Rocks

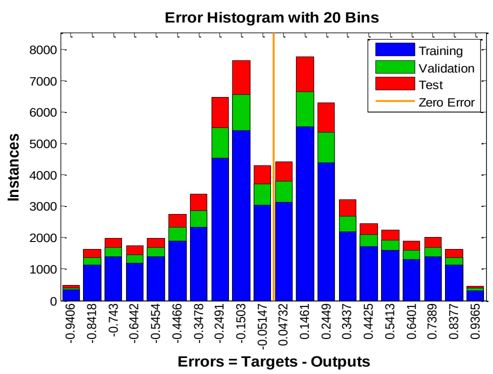

Fig. 5. Shows the First Error Histogram

Fig. 6. Displays the Confusion Matrices of Clastic and Carbonate Rocks

Fig. 7. Shows the Second Error Histogram

Fig. 8. Shows Confusion Matrices of Sand and Sandstone

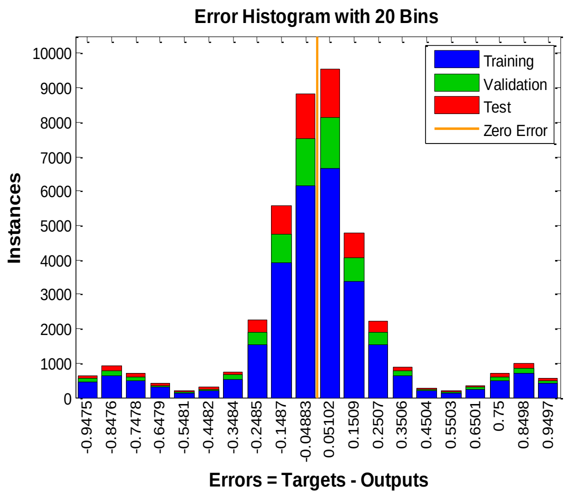

Fig. 9. Shows the Third Error Histogram

Fig. 10. Shows Confusion Matrices of Dolomite and Limestone

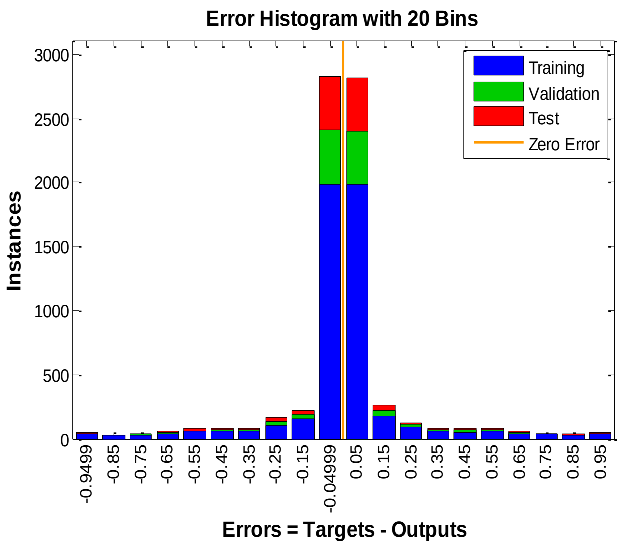

Fig. 11. Shows the fourth error Histogram

Table 2. Shows The accuracy of The PRA Approach

	Training	Validating	Testing	Overall
Permeable / **Unpermeable**	76.3	76.9	75.2	76.2
Clastic / **Carbonate**	94.9	94.3	95.2	94.9
Sand / **Sandstone**	86.2	86.6	85.9	86.2
Dolomate / **Limastone**	92.8	93.2	92.3	92.8

Table 3. Comparing the accuracy of the PRA Approach with machine learning model

	Al-khudafi (2023)	This study (overall)	This study (AAPRE)
Permeable / **Unpermeable**	0.87%	76.2%	23.8
Clastic / **Carbonate**		94.9%	5.1
Sand / **Sandstone**	0.90% / 0.83%	86.2%	13.8
Dolomite / **Limestone**	0.88% / 0.91%	92.8%	7.2
No. of Data	20966	32000	

6- Conclusion

- The pattern recognition approach (PRA) performs well in the prediction of the lithology of the Camaal oil field.
- The proposed model achieved more accurate and reliable for prediction lithology and can be used in wide range and for other carbonate oil fields.
- The accuracy of the pattern recognition approach decreases with increasing input data. This approach does not take a long time compared with conventional methods.

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نهج التعرف على الأنماط (PRA) لتحديد الصخور في مكامن النفط في حقل كمال النفطي، اليمن

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الخلاصة

لا يزال التحديد الدقيق لخصائص صخور الخزان يمثل تحديًا في هندسة البترول. هناك بعض التقنيات التقليدية المتاحة لتحديد الصخور. ومع ذلك، فإن تطبيق تلك التقنيات كان طويلا ومعقدا. لذلك، فإن الهدف الرئيسي من هذه الدراسة هو تبسيط عملية تحديد صخور المكمن. تقدم هذه الورقة طريقة التعرف على الأنماط (PRA) لتحديد صخور المكمن ببساطة ودقة. وقد تم اختيار أربعة آبار من حقل كامال لتطوير هذا النهج. تمت رقمنة حوالي ٣٢٤٠٠ نقطة بيانات من الآبار السابقة. استخدم نهج PRA العمق وأشعة جاما وعلم الصخور والصوت والنيوترون وسجلات الكثافة كمدخلات. تم تصنيف البيانات إلى ثلاثة أجزاء: ٧٠% كبيانات تدريب و١٥% كبيانات اختبار و١٥% كبيانات للتحقق، أظهرت النتائج أن النهج المقترح يوفر تنبؤًا مناسبًا للحجريات بدقة أعلى مقارنة بالحجريات الفعلية.

الكلمات الدالة: الشبكة العصبية الاصطناعية، الصخور المكمنة، النموذج الاصطناعي، أنواع الصخور، التعرف على الصخور.