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Research Paper

Estimation of Young's Modulus Using Petrophysical Logs and Deep Learning Algorithms in One of Iran's Hydrocarbon Fields

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Abstract: Young's modulus is one of the important parameters in geomechanical and petrophysical modelling, which is an indicator of rock hardness. Calculation of this parameter is one of the basic prerequisites for analyzing the stability of the well wall during the drilling of oil and gas wells. Many experimental models have been introduced to determine Young's modulus; each of them is used for a specific area. One of the recently used methods is intelligent methods. In this study, an attempt has been made to predict dynamic Young's modulus using deep learning algorithms in one of the hydrocarbon reservoir wells in southwest Iran. In order to use deep learning algorithms, it is first necessary to determine the effective features to estimate the Young's modulus as input of the algorithms. In this article, Pearson's correlation coefficient was used to select these features. In the following, Young's modulus was estimated using CNN+LSTM and LSTM+MLP hybrid networks, and their coefficient of determination (R2) values were determined to be close to 1, and the prediction error of both algorithms was very low for training and test data. Moreover, to ensure the results of the algorithms, a part of the data was set aside as blind data, and the error and R2 values were calculated for it. The mean square error (MSE) of the LSTM+MLP and CNN+LSTM hybrid algorithms was obtained as equal to 30.51 and 25.99, and their R2 values were determined as 0.77 and 0.81, respectively. The results show the effectiveness of deep learning algorithms introduced in predicting Young's modulus, but comparing the two presented algorithms, the CNN+LSTM algorithm has higher accuracy and less error.

Keywords: Young's modulus, petrophysical data, CNN+LSTM algorithm, LSTM+MLP algorithm, Model evaluation.

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INTRODUCTION

Information on rock mechanical properties of hydrocarbon reservoirs has an impact on decision-making in drilling operations, well completion, well stimulation, etc. [1]. One of the important parameters in rock mechanics is Young's modulus, which is actually an indicator of the rock's strength against strain, or in other words, an indicator of the rock's hardness [2]. Young's modulus is one of the elastic parameters of rock, which is divided into two types, static and dynamic, depending on the method of its determination. The static tests that are performed on the samples taken from the formations obtain the values of the static Young's modulus by measuring the deformation of the rock under pressure. Static tests require direct sampling from the desired area, and special laboratory equipment is needed to achieve good results [3]. Therefore, due to the high cost and time required in this method, it is not possible to obtain the static Young's modulus values for all depths of underground formations directly using laboratory methods. On the other hand, the dynamic method is simpler, less costly and requires less time. In this method, a continuous profile of elastic parameters under in-situ conditions is obtained according to seismography or well drilling. In addition to Young's modulus, he obtained some other rock-mechanic parameters, such as shear modulus, bulk modulus and Lame coefficient, by using the velocity of longitudinal and shear waves [4]. Equation 1 shows dynamic Young's modulus (Edyn) using logs of density (ρ), shear wave velocity (Vs) and compressional wave velocity (Vp) [5].

$$E_{dyn} = \rho {V_s}^2 \frac{3V_p^2 - 4V_s^2}{V_p^2 - V_s^2} \tag{1}$$

METHODS

In this article, the data of RHOB, CHAL, NEUT, LL7, PEF, Vp, Vs, MLL, and GR logs were available to determine the Young's modulus using deep learning algorithms.

In order to select the effective features and suitable inputs for the algorithms, the correlation coefficient of the features should be checked with the Young's modulus. One of the methods of selecting the feature is to calculate the Pearson correlation coefficient. According to Pearson's correlation, Vp, RHOB, and NEU logs were selected as the input of the algorithms, and adding other logs increases the error and decreases the accuracy. Figure 1 shows the selection of features using the Pearson correlation matrix.

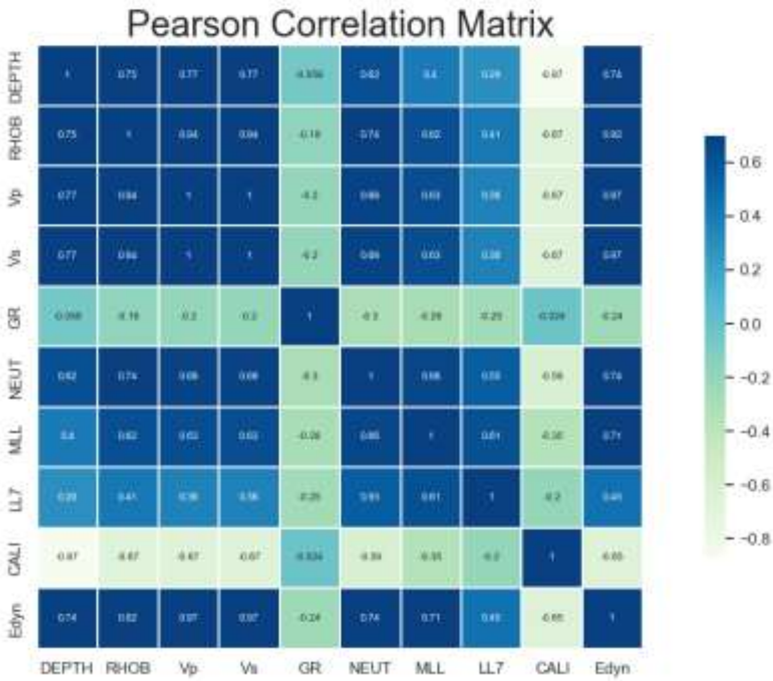


Figure 1. Selection features using Pearson correlation matrix

In the following, the total data was 8591 data, and from the beginning, 1634 data were left as blind data to ensure the results of the algorithm, and the other data were divided into two parts, training and testing, and 80% of the data (5565 data) were used for training. And 20% of the data (1392 data) were divided into tests. In the next step, data normalization has been done to achieve higher accuracy. For normalization, the min-max normalization function is used, which adjusts the available data between zero and one. In the following, the Adam optimizer function is used for optimization. To evaluate the model and compare the results of deep learning algorithms, RMSE error, MSE error and R^2 have been used, and their relationships are according to equations 2, 3 and 4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Z_{mesured} - Z_{predict})^2 \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Z_{mesured} - Z_{predict}\right)^2}{\sum_{i=1}^{n}\left(Z_{mesured} - Z_{average}\right)^2} = 1 - \frac{MSE}{\sigma^2} \tag{4}$$

FINDINGS AND ARGUMENT

In this article, the results of two deep learning algorithms, including LSTM+MLP and CNN+MLP, were investigated, MSE error, RMSE error and R^2 were calculated for training, testing and blind data. Table 1 displays Young's modulus prediction errors and accuracies based on the test (20%) subset, respectively.

Figure 2 shows the comparison of Young's modulus predicted and Young's modulus measured for training and test data.

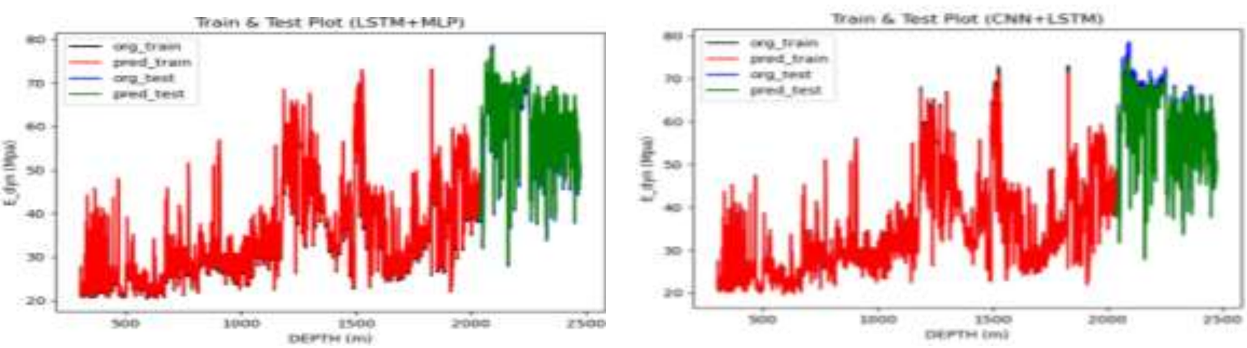
Tables 2 displays the Young's modulusprediction errors and accuracies based on the blind subsets, respectively.

Table 1. Young's modulus prediction errors and accuracy for test data records using a deep learning algorithm

Deep learning models	MSE	RMSE	R^2
LSTM+MLP	1.0650	1.0320	0.9857
CNN+LSTM	0.5760	0.7589	0.9923

Table 2. Young's modulus prediction errors and accuracy for blind data records using deep learning algorithms

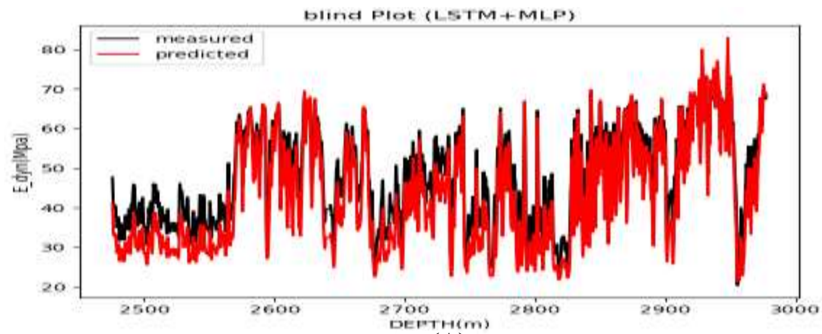
Deep learning models	MSE	RMSE	R^2
LSTM+MLP	30.5101	5.5235	0.7733
CNN+LSTM	25.9923	5.0982	0.8069



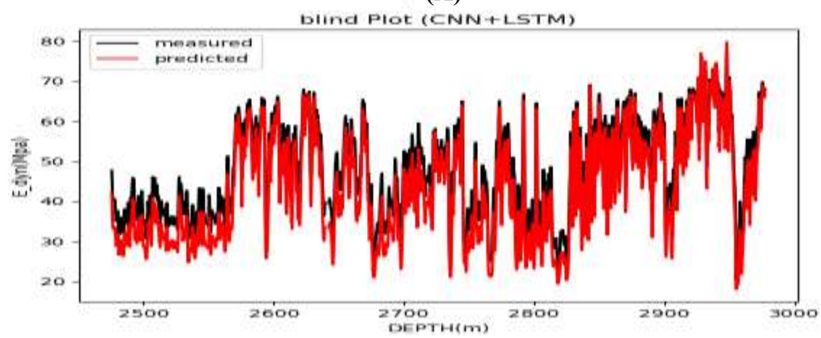
(A) **(B)**

Figure 2. Display of Young's modulus prediction using deep learning algorithms for training and testing data; **A:** Young's modulus prediction for train and test data using the LSTM+MLP algorithm, **B:** Young's modulus prediction using CNN+LSTM [Black log (Young's modulus measured for training (original data)), red log (Young's modulus predicted for training data), blue log (Young's modulus measured for test data (original data)), and green log (Young's modulus predicted for test data)]

Figure 3 shows the comparison of Young's modulus predicted and Young's modulus measured for blind data.



(A)



(B)

Figure 3. Display of Young's modulus prediction using deep learning algorithms for blind data; **A:** Young's modulus prediction using LSTM+MLP, **B:** Young's modulus prediction using CNN+MLP [Black log (Young's modulus predicted), red log (Young's modulus measured)]

CONCLUSIONS

Considering the importance of Young's modulus in determining geomechanical and petrophysical models, it is necessary to use a cheap and accurate method to predict Young's modulus. For this purpose, deep learning and LSTM+MLP and CNN+LSTM algorithms have been used in this study to estimate Young's modulus. In order to apply the algorithm on the data, it is necessary to first determine the effective and influential characteristics on Young's modulus. In this article, the effective characteristics were determined using the Pearson correlation coefficient, and the logs of Vp, RHOB, and NEUT were identified as the input of the algorithms. In the following, the introduced models were applied, and RMSE, MSE and R2 were calculated to evaluate the results of the models. The comparison of the results shows that both algorithms have obtained good results for training and test data, and for blind data, the CNN+LSTM algorithm performs better than the LSTM+MLP algorithm for It has Young's modulus prediction because it has a lower error and a higher coefficient of determination compared to the LSTM+MLP algorithm. So, it can be said that deep learning algorithms can be used as an effective, simple and low-cost method to estimate elastic modulus and especially Young's modulus using logs.

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