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RESEARCH ARTICLE

Estimation of density log and sonic log using artificial intelligence: an example from the Perth Basin, Australia

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Abstract

It is well understood that with a large number of data, an excellent interpretation of the subsurface condition can be produced, and also our understandings of the subsurface conditions can be improved significantly. However, having abundant subsurface geological and petrophysical data sometimes may not be possible, mainly due to budget issues. This situation can generate issues during hydrocarbon exploration and/or development activities.

In this paper, the authors tried to apply artificial intelligence (AI) techniques to estimate outcomes values of particular wireline log data, using available petrophysic data. Two types of AI were selected and these are artificial neural network (ANN), and multiple linear regression (MLR). This research aims to advance our understanding of AI and its application in geology. There are three objectives of this study: (1) to estimate sonic log (DT) and density log (RhoB) using different types of AI (ANN and MLR); (2) to assess the best AI technique that can be used to estimate certain wireline log data; and (3) to compare the estimated wireline log values with the real, recorded values from the subsurface.

Findings from this study show that ANN consistently provided a better accuracy percentage compared to MLR when estimating density log (RhoB). While using different set of data and technique, estimation of sonic log (DT) produced different accuracy level. Moreover, crossplot validation of the results show that the results from ANN analysis produced higher trendline reliability (R^2) and correlation coefficient (R) than the results from MLR analysis. Comparison of the estimated RhoB and DT log data with the original recorded data shows minor mismatch. This is evident that AI technique can be a reliable solution to estimate particular outcomes of wireline log data, due to limited availability of the original recorded subsurface petrophysic data. It is expected that these findings would provide new insights into the application of AI in geology, and encourage the readers to explore and expand the many possibilities of the application of AI in geology.

Keywords: Wireline log data, Hydrocarbon, Artificial intelligence (AI), Artificial neural network (ANN), Multiple linear regression (MLR)

1. Introduction

A successful oil and gas exploration, production, and development activities may rely on the availability of subsurface data (e.g. petrophysics data, seismic data, among others) and an excellent subsurface interpretation, besides the presence of a working petroleum system. Having a significant number of subsurface data is important in order to have a better insights and understanding of the source rocks, reservoirs, and cap rocks, to avoid failures in the exploration and/or development activities. Petrophysics data, which are a record of subsurface rock's petrophysical properties are considered as an important data needed to gain insights into the subsurface (Cannon, 2016). Due to budget limitation, however, many oil and gas companies sometimes decided not to record a complete, full set of petrophysics/wireline log data during the exploration and/or development stage. A limited type and number of wireline log data may affect the interpretation of the subsurface rocks and conditions, and could cost a significant lost to the oil and gas companies.

Artificial intelligence (AI) may provide a solution to the limited subsurface wireline log data. This technique can estimate values of certain petrophysical properties using available dataset, either from the same well, or from the vicinity wells (Lv et al., 2021). The application of AI in geology is still limited, with a few authors have successfully applied this technique for various geological purposes (e.g. Tariq et al., 2019; Lv et al., 2021; Pang et al., 2021; Zheng et al., 2021). This relatively new technique can help in providing estimated values for certain type of wireline log data, and hence contribute to a better subsurface interpretation, and a successful hydrocarbon exploration, production, and development activities.

AI has been successfully applied to the field of geology for various purposes. AI can help denoise seismic data in a supervised fashion (Birnie et al., 2021), to determine reservoir rock properties (Cuddy, 2021), to optimise drilling operation, and to improve hydrocarbon recovery (Solanki et al., 2022), and for mineral prospectivity mapping (Sun et al., 2019). Moreover, AI can also be used to estimate elastic properties of rock for geo-engineering purposes (Tariq et al., 2019), and to predict tunnel geology, its construction time and costs (Mahmoodzadeh et al., 2020). There are many other applications of AI in geology that are not possible to be mentioned in this paper/section. A better understanding of this techni-que may also unlock the application of this method to provide solution to many other geology-related problems.

This paper aims to better understand the application of AI in geology. There are three objectives of this study: (1) to estimate sonic log (DT) and density log (RhoB) using different types of AI (artificial neural network (ANN) and multiple linear regression (MLR); (2) to assess the best AI technique that can be used to estimate certain wireline log data; and (3) to compare the estimated wireline log values with the real, recorded values from the subsurface. It is expected that the results from this study would improve our understanding of the AI techniques, its application in petrophysical analysis, and how this AI technique could help and assist geoscientists in analysing and interpreting subsurface conditions.

2. Data and methods

The data used in this study are from three wells located onshore of the northern Perth Basin, Western Australia. Original well's name have been changed, due to confidentiality issues, and these wells were renamed to Well-A, Well-B, and Well-C. These studied wells are situated close to each other, within the radius of 10 km. Wireline logging data from Well-A and Well-B include neutron porosity log (NPHI), gamma ray log (GR), density log (RhoB), and sonic log (DT). While data from Well-C include neutron porosity log (NPHI) and gamma ray log (GR). This study decided to estimate RhoB and DT using AI techniques, due to the importance of these logs to support the interpretation of the subsurface, and because Well-C does not have these two logs. All the aforementioned wireline logging data used in this study are the data of the Late Permian Beekeeper Formation, a proven mixed carbonate-siliciclastic reservoir in the northern Perth Basin, Western Australia (Crostella, 1995; Mory and Iasky, 1996; Norvick, 2004; Thomas, 2014).

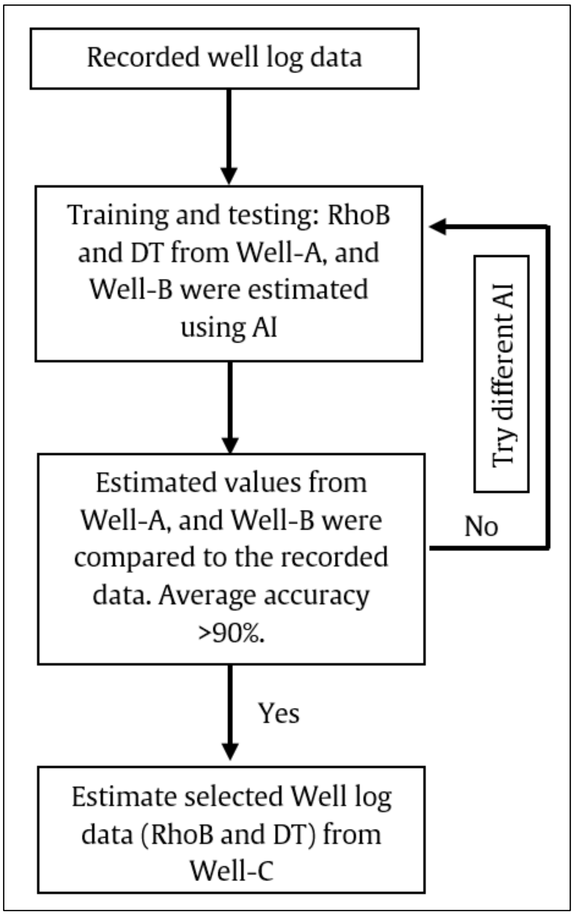

Fig 1. Workflow used in this study to estimate RhoB and DT from the available dataset.

Two types of AI techniques were used to achieve the aim and objectives of this study, which are artificial neural network (ANN), and multiple linear regression (MLR). ANN and MLR techniques were selected due to their excellent ability to estimate certain outcome values by relying on the input data (multiple type of data), with high level accuracy. Processing of the data using these techniques were conducted using SPSS-IBM software. Workflow of how these methods used for this study is shown in fig.1. Visualisation of the data and results of this study were carried out with the help of Microsoft Excel and Adobe Illustrator.

ANN is an AI method that tries to mimic how human brain analyses and processes data (Gurney, 2004). This method builds several processing units based on interconnected connections and consists of an arbitrary number of cells or nodes or units or neurons that connect the input set to the output (Dastres and Soori, 2021). ANN acquires the knowledge of the model, and discover the structure of the data through training, and then apply it to unknown data for the purpose of classification, prediction, time series analysis, etc (Wesolowski and Suchacz, 2012). ANN is better than traditional computers in processing the data because it can adapt to new environments by learning, can process fuzzy (imprecise) data, can work with noisy or erroneous data, and can perform classification tasks very quickly (Buscema, 1998).

MLR is a statistical technique that uses several explanatory variables to predict the outcome of a response variable (Uyanık and Güler, 2013). MLR technique uses correlations between variables (this study: input well log data) to explain variance in outcome variables and predict specific outcome values (Abbott, 2017). This MLR technique allows us to investigate how a set of explanatory variables is associated with a dependent variable of interest, but does not allow us to make causal inferences (Tranmer and Elliot, 2008).

3. Geological settings

The Perth Basin is an elongate, north-south trending trough underlying approximately 100,000 square kilometres of the Western Australian margin between Geraldton and Augusta (Fig.2). Slightly more than half the basin lies offshore in water depths of up to 1,000 m (Mory and Iasky, 1996). The Perth Basin consists of a series of northerly striking sub-basins, troughs and uplifts, and covers an area of ca. 45,000 km^2 onshore and 55,000 km^2 offshore (Song and Cawood, 2000). To the north, the basin is bounded by the Northampton block and the eastern margin of the Perth Basin is defined by the Darling Fault (Thomas, 2014). To the south, the Harvey Ridge, another shallow basement feature, extends obliquely northwest from the Darling Fault and separates the Dandaragan Trough from the Bunbury Trough, and Westward, sediments thicken into the Vlaming Sub-basin (Cadman et al., 1994). It is possible that a northwest extension of the Precambrian Leeuwin Block and a fault system extending southwest from the Edward's Island Block, merge to form the western boundary of the Vlaming Sub-basin (Cadman et al., 1994).

Strata within the Perth basin range mainly from Permian to Cretaceous in age and locally reach up to 15,000 m in thickness in major depocentres like the Dandaragan Trough (Song and Cawood, 2000). Basement of the Perth basin consists of Archaean and Proterozoic blocks, overlain by an Early Paleozoic sequence (Tumblagooda Sandstone), recognised in the northern part of the basin and probably coincided with local block faulting (Song and Cawood, 2000; Song and Cawood, 2010).

The Perth Basin developed through the interplay of phases of extension and transtension, resulting in a complex history of faulting and synsedimentary fault block movement (Mory and Iasky, 1996; Norvick, 2004; Thomas, 2014). Two main rifting phases in the Permian and Jurassic to earliest Cretaceous have been recognised in both offshore and onshore (Mory and Iasky, 1996; Song and Cawood, 2000). The younger event corresponds to final rifting and breakup of Gondwana lithosphere between Australia and Greater India and, entails dextral strike–slip deformation and basin inversion as well as margin orthogonal extension (Norvick, 2004; Thomas, 2014; Geoscience-Australia, 2020).

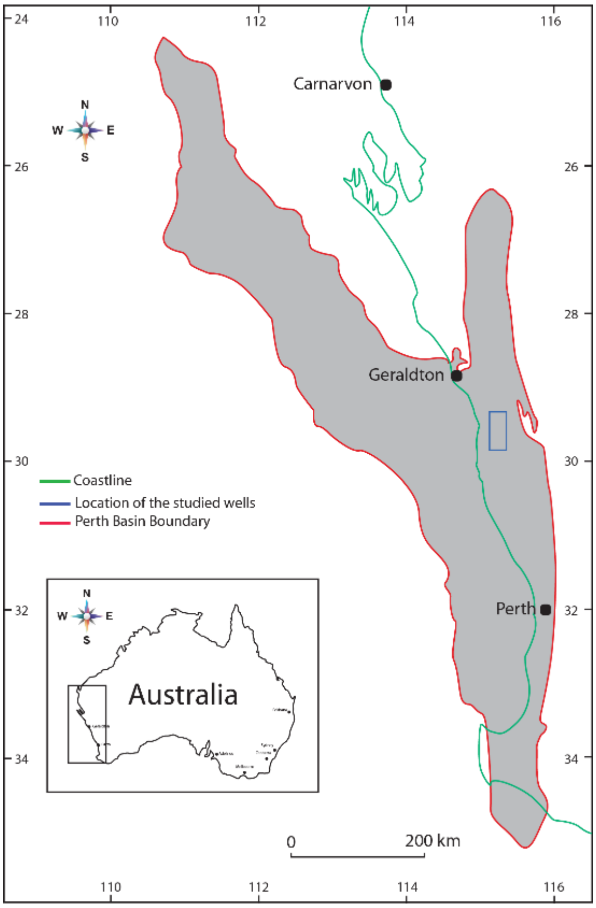

Fig 2. The Perth Basin is situated in the Western Australia, with more than half the basin lies offshore (Modified from Sharifzadeh and Mathew, 2011).

Most hydrocarbon accumulations in the Perth Basin are in structures associated to strike–slip deformation, although rollover anticlines have also proved as successful exploration sites (Crostella, 1995). Basement structures have been reactivated during basin formation and control the linear, north-striking structural grain of the basin (Song and Cawood, 2000). The basin is compartmentalised by a series of northwest-striking transfer faults which formed during break-up (e.g. Abrolhos and Cervantes transfer zones), but which were probably localised along pre-existing basement structures (Mory and Iasky, 1996).

4. Results

The application of AI techniques to estimate density log (RhoB) and sonic log (DT) using input data of neutron porosity log (NPHI), and gamma ray log (GR) as the independent variables/covariates yielded excellent results (Fig.3, and 4), with average accuracy of >95% (table 1), and crossplot validation showing trendline reliability (R^2) and correlation coeffcient (R) values of more than 0.6 (Fig.5, and 6). The accuracy percentage of the results of each sample data was calculated using the ABS function in Microsoft Excel, while R was calculated using the CORREL function.

Findings of this study consistently show that ANN produced better results compared to MLR when estimating RhoB (table 1, Fig.5, and 6), either using the input data from Well-A or Well-B. This suggests that ANN is more reliable when used to estimated RhoB. The accuracy of the estimated RhoB values is ranging between 74.9%-100%, with the average accuracy value between 97.98%-98.87% (table 1). In Well-A, the average accuracy of RhoB using ANN is 98.47%, slightly higher than the 97.98% accuracy of MLR (table 1). Moreover, the average accuracy of RhoB in Well-B using ANN, which is 98.87%, is also slightly higher compared to 98.85% of MLR (table 1).

The accuracy for the estimated DT values is not consistent, as different dataset and AI techniques produced different accuracy level (table 1). Accuracy for estimated DT from Well-A is ranging between 78.18%-99.99%, with average value ranging between 96.03%-96.08% (table 1). These results from Well-A show that MLR is a better choice when estimating DT values. However, results from Well-B show that ANN produced a better results and accuracy compared to MLR when estimating DT values. The accuracy of the estimated DT value from Well-B is ranging between 79.29%-99.99%, with the average value ranging between 96.88%-96.98% (table 1).

Crossplots analysis between the recorded DT and RhoB and the estimated DT and RhoB, from both Well-A, and Well-B were conducted to validate the application and results of AI methods (Fig.5, and 6). The results show that the R^2 (trendline reliability) and R (correlation coefficient) values of the studied data are more than 0.6 (except Fig.5.D), and these are considered as good-excellent results (Fig.5, and 6). The nearer R^2, and R are to 1, the better the trendline fits the data/better correlation between the data. Moreover, results from crossplot validation show that ANN analysis consistently produced higher R^2 and R, compared to MLR, either in Well-A (Fig.5) or Well-B (Fig.6). This is suggestive that ANN analysis is better than MLR analysis in estimating DT and RhoB. These good-excellent crossplots results validate that the results from AI analysis are reliable and acceptable.

Training and testing of the data from Well-A and Well-B showed high level accuracy results, as has been explained in the earlier paragraphs. On the basis of these excellent results, AI techniques were then applied to estimate RhoB and DT values for Well-C, using the input data from Well-A, Well-B, and Well-C.

Results of this study show that the estimated RhoB and DT of Well-C are similar to the recorded and estimated RhoB and DT from Well-A and Well-B (Fig.7, 8, and 9). Low NPHI (<5%), and low GR (20-40 API) correspond to low DT (<55 US/F). Moderate NPHI (5-10%), and moderate GR (40-60 API) correspond to moderate DT (55-65 US/F). High NPHI (>10%), and high GR (>60 API) correspond to high DT (>65 US/F). On the other hand, the trend for RhoB log is slighly different compared to the trend for DT log. Low NPHI (<5%), and low GR (20-40 API) correspond to low RhoB (<2.6 G/Cm3). Moderate (5-10%) to high (>10%) NPHI, and moderate (40-60 API) to high (>60 API) GR correspond to moderate (2.6-2.7 G/Cm3) RhoB. High NPHI (>10%), and high GR (>60 API) correspond to high RhoB (>2.7 G/Cm3). Therefore, on the basis of these patterns and trends similarities, the authors consider the estimated DT and RhoB values of Well-C are reasonable, reliable, and acceptable (Fig.7).

Comparison of the estimated RhoB and DT values with the recorded data shows a minor mismatch between logs, and shows similar pattern with the original recorded data (Fig.3, and 4). These results are evident that AI techniques (ANN and MLR) are suitable, applicable, and acceptable to be carried out to estimate particular subsurface petrophysical data.

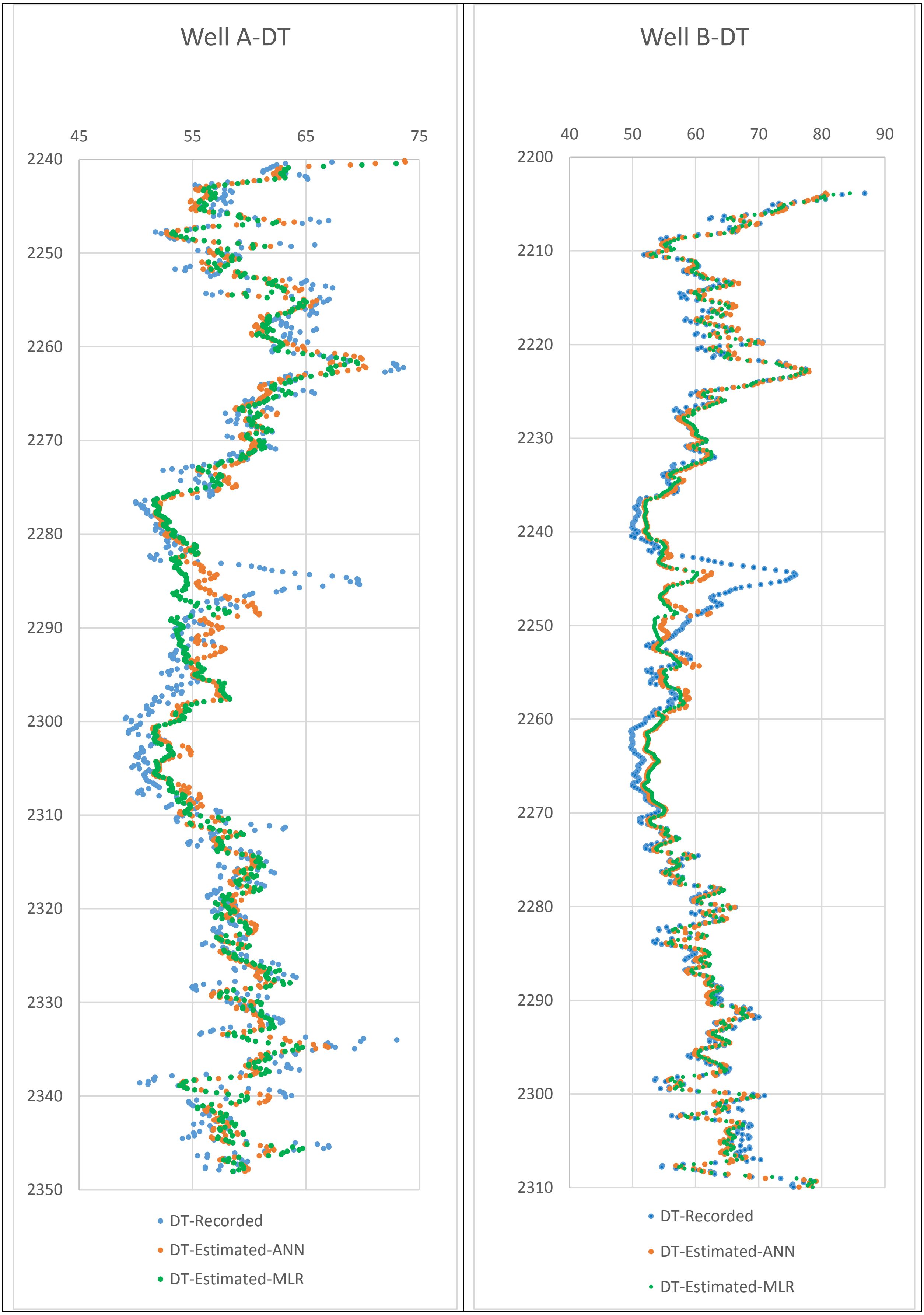

Fig 3. Comparison of the results from AI (ANN, MLR) analysis and the original recorded data. The estimated values of sonic log (DT) of well-A, and well-B are quite similar with the original recorded data. Minor mismatch between the logs can clearly be seen in this figure. Y axis = subsurface depth (m), X axis = sonic log (DT, in US/F).

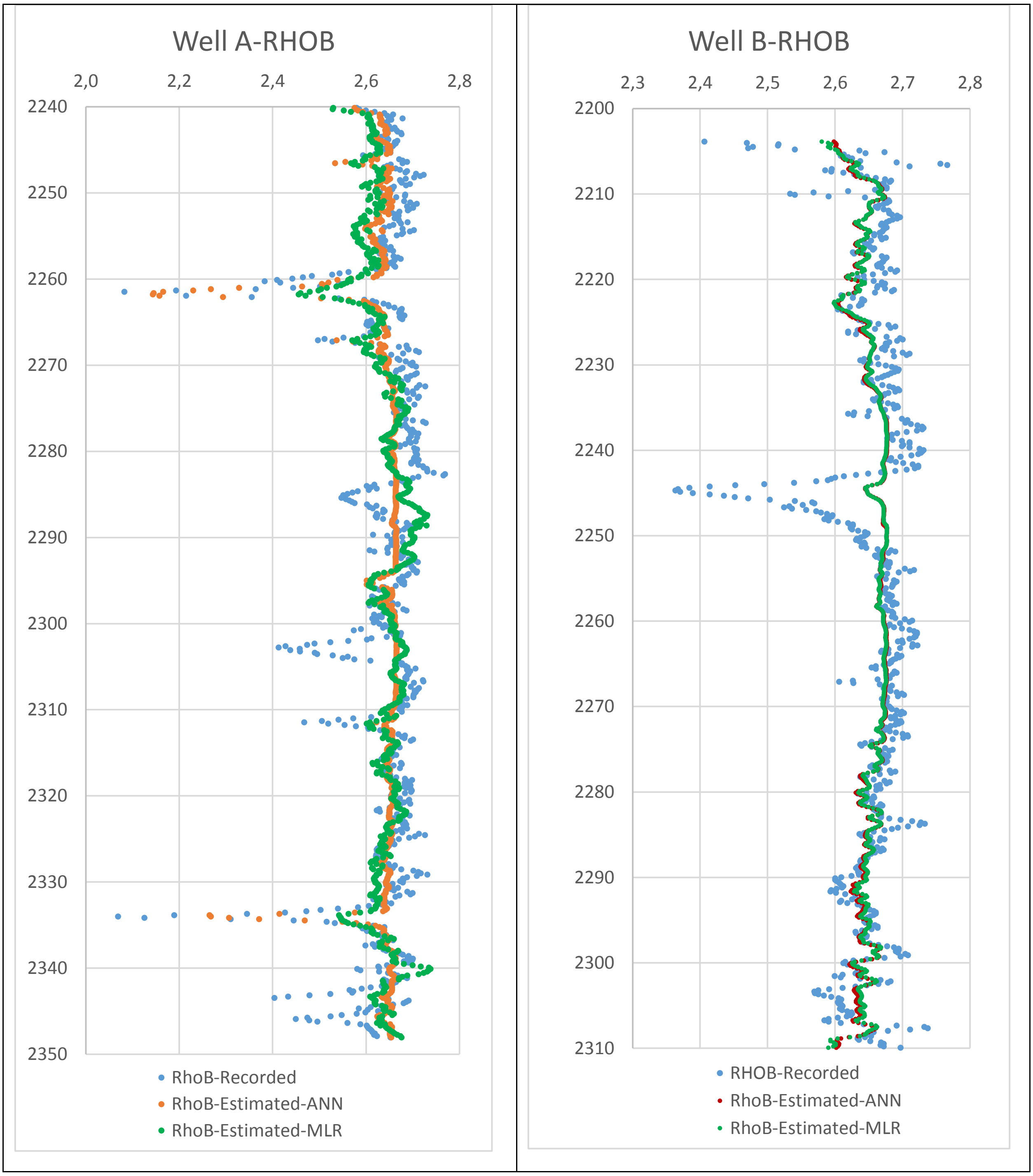

Figure 4. Comparison of the results from AI (ANN, MLR) analysis and the original recorded data. The estimated values of density log (RhoB) of well-A, and well-B are quite similar with the original recorded data. Minor mismatch between the logs can clearly be seen in this figure. Y axis = subsurface depth (m), X axis = density log (RhoB, in G/Cm^3).

Table 1. Accuracy of the AI results are ranging between 74.9%-100%. With this level of accuracy, the results of this AI analysis are considered acceptable and reliable. Accuracy percentage for each sample data was calculated using the ABS function in Microsoft Excel. RhoB = density log (G/Cm^3), DT = sonic log (US/F), ANN = artificial neural network, MLR = multiple linear regression.

	Well-A				Well-B			
	RhoB-Estimated Accuracy (%)		DT-Estimated Accuracy (%)		RhoB-Estimated Accuracy (%)		DT-Estimated Accuracy (%)	
	ANN	MLR	ANN	MLR	ANN	MLR	ANN	MLR
Min	89.53	74.90	79.48	78.18	88.01	87.98	79.29	79.31
Max	99.99	100.00	99.98	99.99	100.00	100.00	99.99	99.99
Avg	98.47	97.98	96.03	96.08	98.87	98.85	96.98	96.88

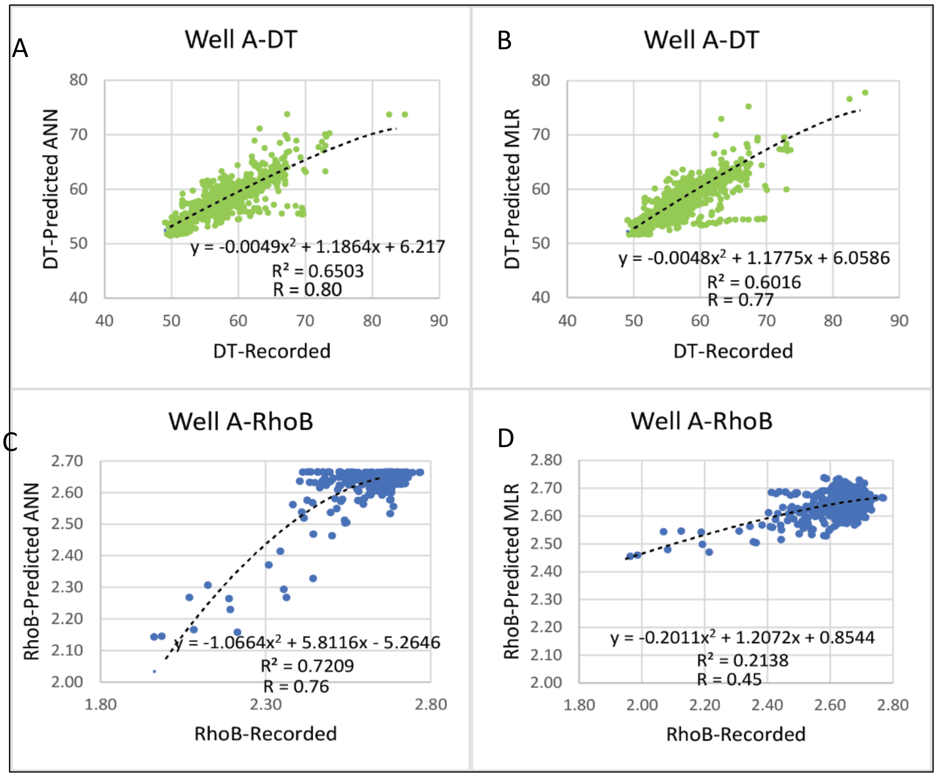

Fig 5. Results from crossplot analysis of Well A. A. Crossplot between recorded DT and estimated DT (using ANN) produced $R^2 = 0.65$, and R = 0.80. B. Crossplot between recorded DT and estimated DT (using MLR) produced $R^2 = 0.60$, and R = 0.77. C. Crossplot between recorded RhoB and estimated RhoB (using ANN) produced $R^2 = 0.72$, and R = 0.76. D. Crossplot between recorded RhoB and estimated RhoB (using MLR) produced $R^2 = 0.21$, and R = 0.45. The nearer R^2, and R are to 1, the better the trendline fits the data/better correlation between the data. R^2 = trendline reliability, and R = correlation coefficient. DT = sonic log (US/F), and RhoB = density log (G/Cm^3).

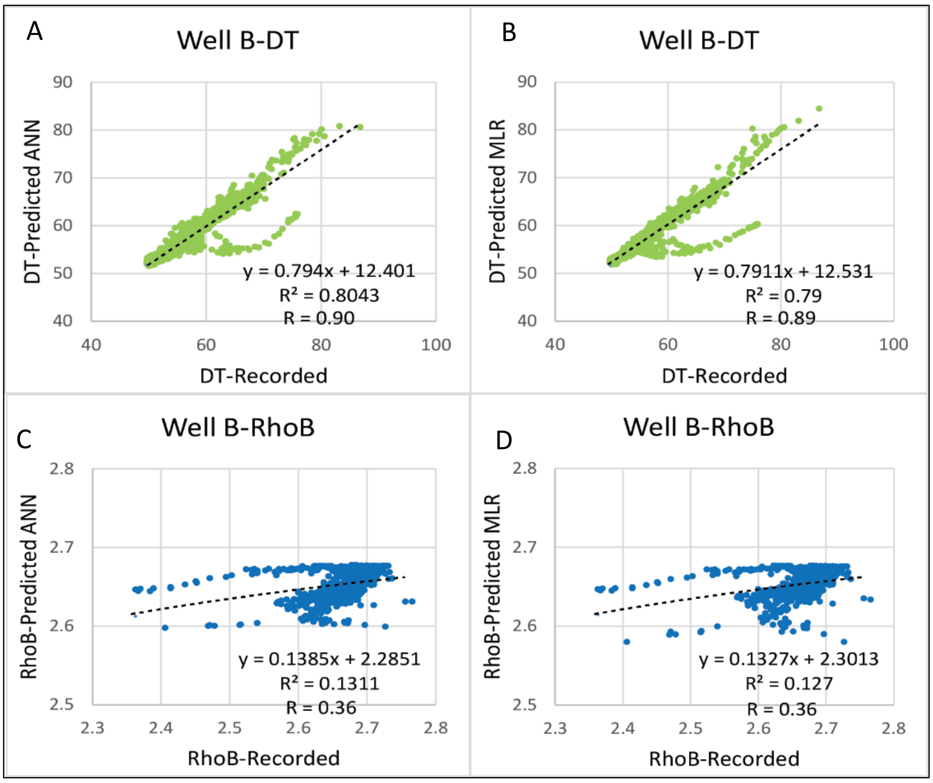

Fig 6. Results from crossplot analysis of Well B. A. Crossplot between recorded DT and estimated DT (using ANN) produced $R^2 = 0.80$, and R = 0.90. B. Crossplot between recorded DT and estimated DT (using MLR) produced $R^2 = 0.79$, and R = 0.89. C. Crossplot between recorded RhoB and estimated RhoB (using ANN) produced $R^2 = 0.13$, and R = 0.36. D. Crossplot between recorded RhoB and estimated RhoB (using MLR) produced $R^2 = 0.13$, and R = 0.36. The nearer R^2, and R are to 1, the better the trendline fits the data/better correlation between the data. R^2 = trendline reliability, and R = correlation coefficient. DT = sonic log (US/F), and RhoB = density log (G/Cm^3).

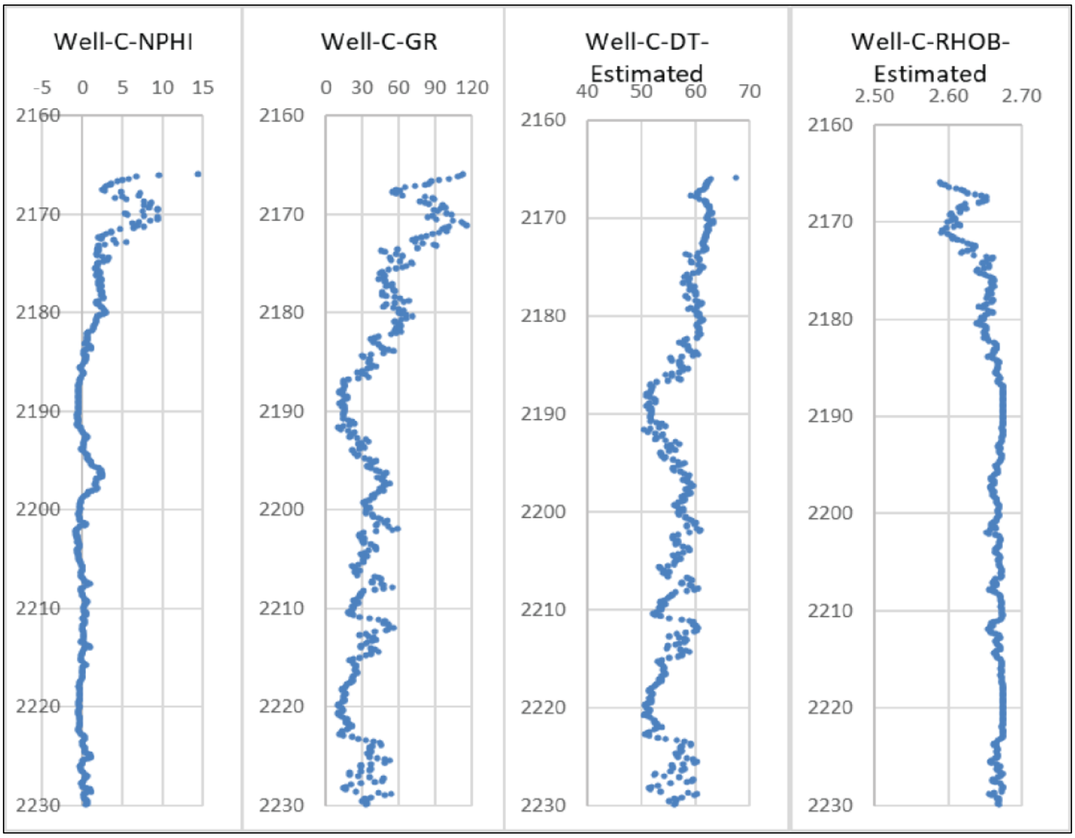

Fig 7. NPHI and GR are the input data used to estimate RhoB and DT of Well-C. The data are from subsurface depth of 2165-2230 m.

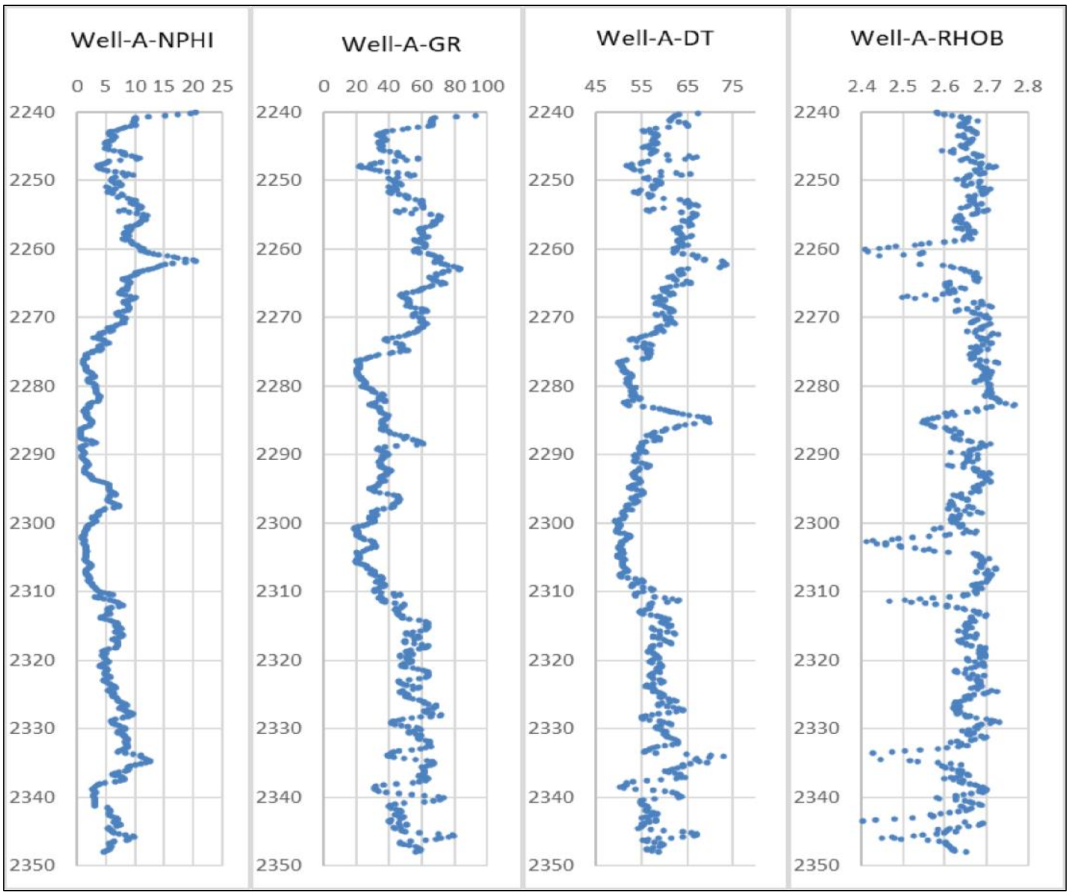

Fig 8. Original recorded wireline log data of Well-A. These data were trained and tested to estimate RhoB and DT. The data are from subsurface depth of 2240-2350 m.

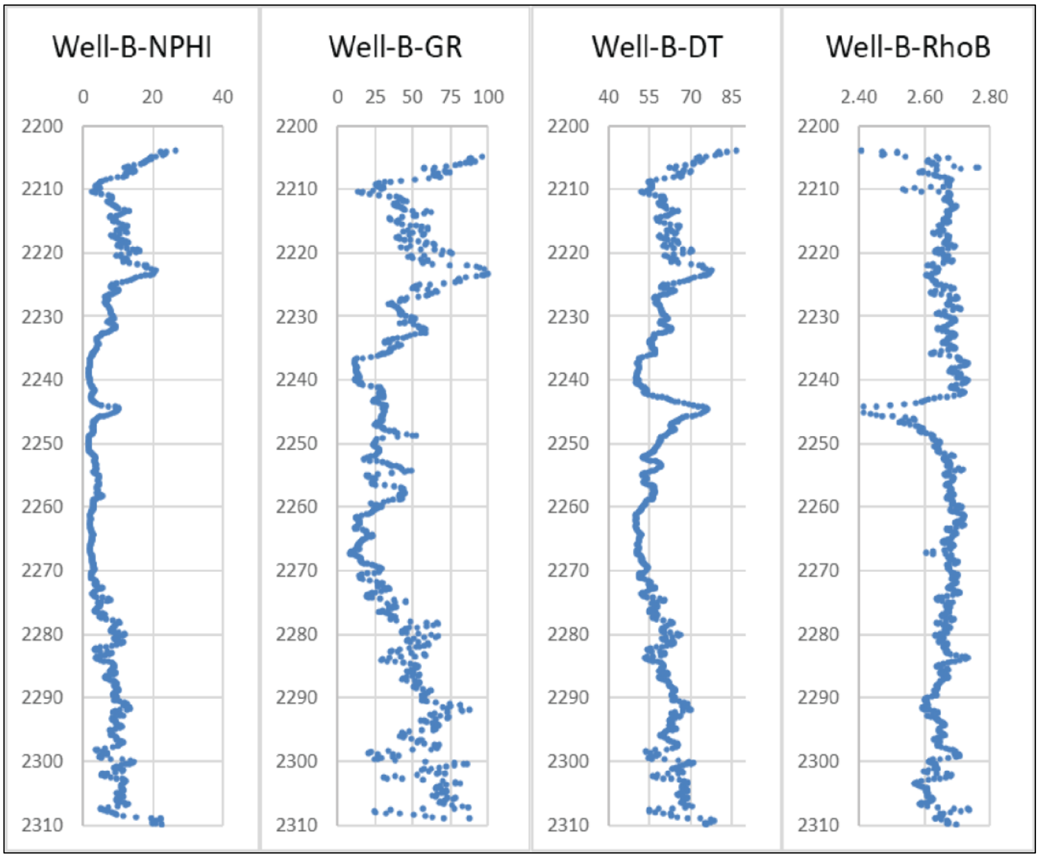

Fig 9. Original recorded wireline log data of Well-B. These data were trained and tested to estimate RhoB and DT. The data are from subsurface depth of 2200-2310 m.

5. Discussion

This paper contributes to the advancement of AI in geology, in particular field of petrophysical analysis. Findings from this study showed the possibility of applying AI to estimate particular wireline log data (RhoB and DT) that yielded high level accuracy results. AI is a relatively new technique that can be used to provide a solution to many problems, in many field of sciences, including geology (Chen et al., 2020). However, the application of this technique in geology is still in its infancy, and much development is needed (Chen et al., 2020).

Findings of this study, using the data from Well-A, Well-B, and Well-C, consistently show that ANN produced better results compared to MLR when estimating RhoB. This is interpreted to be caused by the algorithm of ANN that relies on the deep learning process, multilayer perceptron, with multiple hidden layers, and this makes ANN a more reliable technique compared to MLR. Moreover, data used for this study are subsurface rock data with inconsistent trends/patterns and random relationship between each data, and ANN is best to estimate a particular outcome with the input of this type of data. ANN has an excellent capability (adaptive learning) to identify specific patterns and trends, and in categorising information (Dastres and Soori, 2021).

There is no consistent best techique to estimate DT, as shown by the results of this study. This may be due to the nature of the DT data that are highly sensitive to the type of the subsurface rocks. Vertical distribution of the DT data is highly dispersed, and this make the estimation of this type of data more difficult. Both ANN and MLR may produce DT results with the best/better accuracy level, depending on the type of the input data. These results show that estimating DT needs to be done carefully, and the selection of the AI methods needs to be done with caution. Different AI methods may produce results with different accuracy level for DT estimation.

Comparison of the estimated RhoB and DT with the original recorded RhoB and DT data show a minor mismatch, and the log trends and patterns are quite similar. This is evident that the selected AI methods used for this study (ANN and MLR) are reliable techniques that can produce results with high level accuracy and confident. Although the results from these two analyses are quite similar, the procedure for MLR is much simpler than ANN. Therefore, we encourage the readers to first choose MLR when estimating particular wireline logging data (e.g. RhoB and DT), and if the results are considered as less reliable, then we suggest the reader to apply ANN analysis. It is also a wise choice if the readers decide to run both ANN and MLR analyses simultaneously to compare and see the results from both analyses, as the different algorithm used for each analysis may produce different results.

6. Conclusion

This study provides some new insights into the application of AI in geology, in particular in the field of petrophysical analysis. Problems commonly occur during hydrocarbon exploration and/or development stage, due to the lack of subsurface wireline log data can be tackled by the application of AI techniques to estimate particular well log data. The contribution from this paper is expected to improve our understanding of AI, and encourage the development of AI not only in the field of petrophysics, but also in other branches of geology.

AI, which is a relatively new method, can be used to estimate certain wireline log data using input data of available subsurface petrophysical dataset with high level accuracy and confident. This study used ANN and MLR (types of AI) to estimate RhoB and DT, and it yielded excellent results (average accuracy >95%). ANN is proven to be a better choice when used to estimate RhoB. Besides, results from this study show that both ANN and MLR can produce the best/better results when estimating DT, depending on the type of the input data. Selection of the type of AI technique may need to be done carefully when used to estimate DT.

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