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# Machine Learning-Based Prediction of Shear Wave Velocity: Performance Evaluation of Bi-GRU, ANN, and The Greenberg-Castagna Empirical Method

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**ABSTRACT** - Shear wave velocity (Vs) is recognized as an important elastic parameter for lithology and fluid identification in oil and gas exploration. However, Vs data is not always recorded in well logs. Various empirical approaches are often used to estimate Vs, but these methods show limitations in terms of accuracy and time efficiency. With technological advances, machine learning has become an effective and efficient alternative for predicting Vs from well log data. This study is utilizing the Bi-GRU model, a sophisticated artificial neural network specifically designed to process sequential data. This capability makes Bi-GRU particularly suitable for predicting log Vs data. Four Bi-GRU modeling scenarios are being developed with different hyperparameter configurations and are being compared with ANN models using two input variations: with and without Vp data. The results show that scenario 2 (Bi-GRU with five hidden layers, batch size 64, learning rate 0.005) is achieve the best performance, with $R^2$ values of 0.9787 (without Vp) and 0.9868 (with Vp). The MAE values obtained are being recorded as 9.36 (without Vp) and 11.22 (with Vp). Compared to shows ANN, MLR, and empirical Castagna methods, the Bi-GRU model show a more significant improvement in prediction accuracy. These findings are indicating that Bi-GRU have strong potential for accurately and efficiently predicting Vs from well log data.

**Keywords**: shear wave velocity, machine learning , hyperparameter tuning, gate recurrent unit.



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## INTRODUCTION

Rock elastic parameters, such as compressional velocity (Vp), shear velocity (Vs), and density, play a crucial role in reservoir characterization because they are closely related to rock and fluid properties. Shear wave velocity is a major factor in reservoir prediction and is widely used to analyze lithology, physical characteristics, and to detect and predict the presence of fluids in reservoirs (Feng et al., 2024).

However, shear wave velocity (Vs) data are not always available, even in mature wells or newly drilled wells. Several factors contribute to this limitation, including borehole conditions, restricted logging technology, and high acquisition costs (Wang et al., 2020). Vs is a key parameter in various seismic-based reservoir description processes such as prestack seismic inversion, fluid identification, and amplitude varioation with offset (AVO) analysis (Liu et al., 2023). Consequently, many researchers have methods to predict shear wave velocity using well log data.

In general, the methods used for predictiong shear wave velocity include empirical equations, rock physics modeling, regression-based methods, and machine learning approaches (Fu et al., 2024). The empirical approach is a simple method based on the characteristics of subsurface lithology. However, its dependence on lithology results in reduced accuracy when lithology variation occurs. Rock physics modelling, while more comprehensive, becomes complex when applied to highly heterogeneous formations, as it requires accurate quantification of pore structures and calibration with extensive laboratory data. Machine learning method has recently gained considerable attention due to their ability to process large datasets and model nonlinear relationships between input and target variables. This makes them particularly effective for solving geophysical interpretation problems (Arya et al., 2024). In addition, this technology also allows reservoir quality assessments to be carried out more efficiently in terms of both time and cost (Dixit et al., 2020).

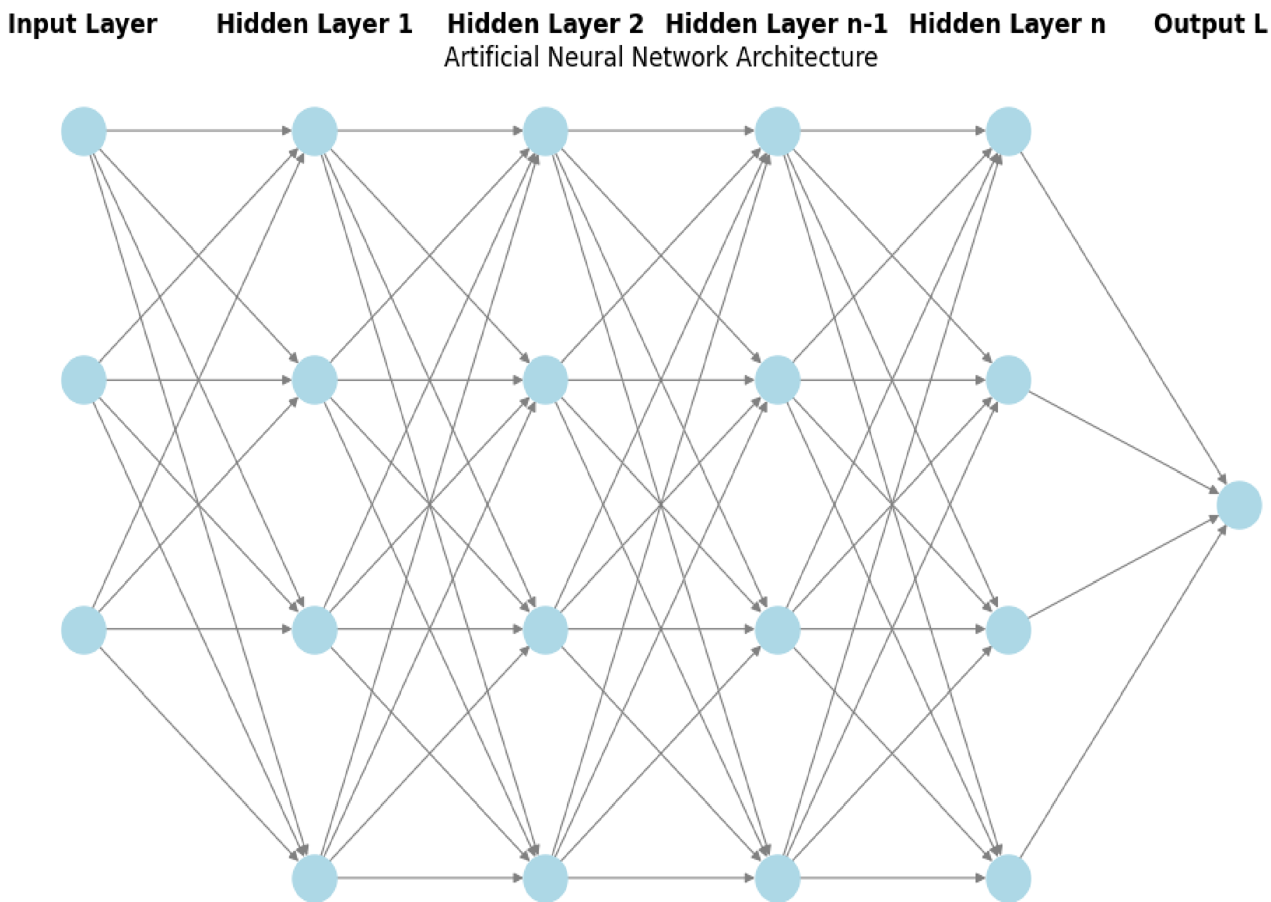


Figure 1. ANN Structure with an input, hidden, output layer. The input layer receives well log data, the hidden layers process nonlinear relationships through neurons and activation functions, and the output layer generates the predicted target variable (shear wave velocity, Vs)

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Advancements in computational efficiency and improved prediction accuracy of various machine learning (ML) methods in recent years have encouraged the widespread application of ML for Vs from well log data. Several previous studies, such as those conducted by Rajabi et al. (2023), Mousavi et al. (2024), Wang et al. (2020), and Fu et al. (2024), have successfully applied ML approach for Vs prediction.

Building upon these developments, this study compares several traditional statistical methods with advanced machine learning architectures to predict Vs from well log data. Generally, the multiple linear (MLR) algorithm is typically used to model linear relationships among well log parameters; however, in reality, not all variables exhibitlinear dependencies. The Artificial Neural Network (ANN) can capture nonlinear relationships between variables (Saputro et al., 2016); however, ANN is not spesifically designed to handle sequntial data with temporal dependencies, making it less effective when temporal patterns are significant.

The Bidirectional Gated Recurrent Unit (Bi-GRU) presents a solution because it is able to capture complex nonlinear relationships while utilizing temporal information more comprehensively (Salehinejad et al., 2017). Therefore, this study applies Bi-GRU to predict Vs and compares its performance with MLR, ANN, and empirical Castagna.

## METHODOLOGY

### Empirical method of castagna

In this study, the prediction of Vs was conducted using the empirical Greenberg-Castagna relationship. The regression coefficient for VS prediction in sandstone based on the Greenberg-Castagna relationship are shown as follows (Taheri et al., 2022):

$$V_s = 0.80416 * V_p - 0.855 \quad (1)$$

where $V_s$ is S-wave velocity and $V_p$ is P-wave velocity.

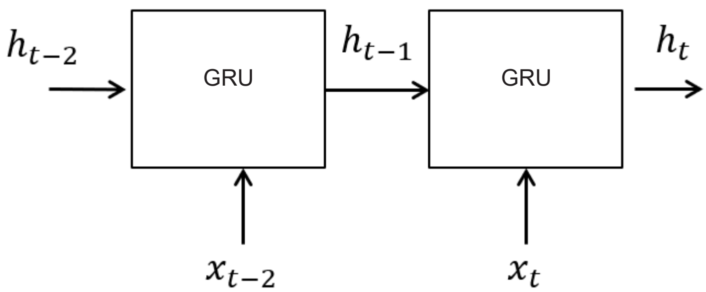


Figure 2. The general topology of the gate recurrent unit.

Table 1. Statistics on well data.

| | DEPTH | RHOB | GR | NPHI | DT:1 | SDT | SW |
|---|---|---|---|---|---|---|---|
| **count** | 801 | 801 | 801 | 801 | 801 | 801 | 801 |
| **mean** | 6.600 | 2388.655 | 102.801693 | 0.24252 | 92.348579 | 170.461403 | 0.794285 |
| **std** | 115.686 538 | 0.085091 | 13.131357 | 0.039777 | 4.784305 | 13.895691 | 0.251189 |
| **min** | 6.400 | 2.112900 | 66.140000 | 0.137 | 78.975100 | 139.763500 | 0.1959 |
| **max** | 6.800 | 2.495600 | 134.897300 | 0.3674 | 108.918800 | 224.003500 | 1.432000 |

**Multiple linear regression**

Multiple Linear Regression (MLR) is an extension of simple linear regression that utilizes more than one independent variable to predict the dependent variable. This allows MLR to capture more complex relationships that may not be observable when only a single predictor is used. By involving multiple input variables, MLR provides more stable and reliable estimates, especially when multivariate relationships exist between parameters (Akhundi et al., 2014).

**Artificial neural network**

Artificial Neural Networks (ANNs) (Figure 1) are layered computational models consisting of interconnected processing units called neurons, arranged in an input layer, one or more hidden layers, and an output layers (Gomaa et al., 2024). ANNs are inspired by the structure and function of biological neural networks and are designed to model complex, nonlinear relationship between input and output data (Wardhana et al., 2021). The basic component of the ANN is the artificial neuron. An artificial neuron is a mathematical function whose inputs are weighted separately and their sum is given through a transfer called weight. The neuron calculates its internal state by summing the weighted products of the input vector and a numerical parameter called bias. This sum is passed through a nonlinear function, which scales all possible values of the internal state into the desired output value interval (Lishner and Shtub, 2022). This process can be represented by the following in Equation 2 (Fu et al., 2024),

$$Y_j^l = \sigma(\sum(W_{ij}^l X_i^{l-1}) + b_j^l) \tag{2}$$

where $Y_j^l$ represents the value of the $j$ neuron in the $l$ layer. $X_i^{l-1}$ represents the value of the $i$ neuron in the previous layer ( $l$ – 1). The weight matrix in the $l$ layer is expressed as $W_{ij}^l$, while $b_j^l$ is the corresponding bias value. The sigmoid activation function is denoted by $\sigma$.

**Gate recurrent unit**

The Gated Recurrent Unit (GRU) is a variant of Recurrent Neural Network (RNN) developed to overcome the vanishing and exploding gradient problems that often occur during the training of conventional RNNs (Fu et al., 2016). The implementation of unique threshold and state memory strategies enables GRU to demonstrate excellent generalization performance in analyzing and processing time series data. (Yu et al., 2023).

The forward transmission process on GRU is as follows:

$$z_t = \sigma(W_z x_t + U_z x_{t-1}) \tag{3}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \tag{4}$$

$$h_t = \tanh\,[W_h x_t + U_h(r_t h_{t-1})] \tag{5}$$

$$h_t = (1 - z_t) \times h_{t-1} + z_t \times h_t \tag{6}$$

where are update gate and are reset gate. and are the input and state information at the current t-moment. and are weights of the update gate. and are weights of the reset gate. Tanh is hyperbolic tangent activation function. are sigmoid activation function (Wang et al., 2022).

The GRU neural network was developed as an improvement of RNN to overcome the vanishing gradient problem, thereby increasing both prediction accuracy and efficiency in the model training process. The cell unit in the GRU neural network is designed

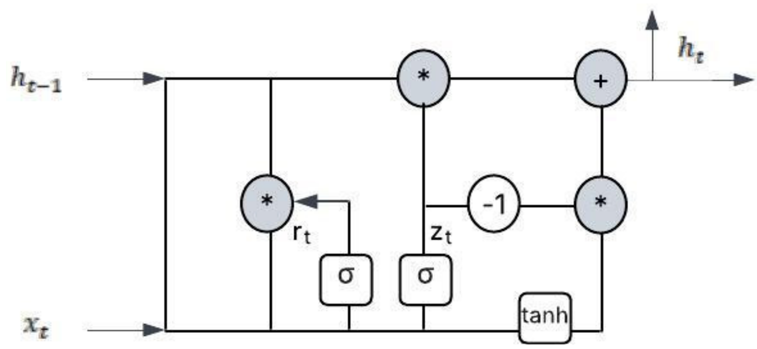


Figure 3. Internal structure of the Gated Recurrent Unit (GRU), showing the reset gate ($r_t$) and update gate ($z_t$) that control information flow and update the hidden state ($h_t$) for sequential data processing.

to improve prediction accuracy and computational efficiency through more optimal update and reset mechanisms in the gating process (Hua et al., 2024).

The topology of the GRU is shown in Figure 2. While a unidirectional GRU architecture is able to capture temporal dependencies from past observations, it is limited in its ability to account for contextual information from future time steps. To address this limitation, BiGRU combines the outputs of two GRU layers that process the sequence in forward and backward directions (Liu et al., 2024). The formula for the GRU Bi is shown in the equation (7) – (9).

$$\overrightarrow{h_t} = \mathrm{GRU}_{fwd}(x_t, \overrightarrow{h}_{t-1}) \tag{7}$$

$$\overleftarrow{h_t} = \mathrm{GRU}_{bwd}(x_t, \overleftarrow{h}_{t-1}) \tag{8}$$

$$h_t = \overrightarrow{h_t} \oplus \overleftarrow{h_t} \tag{9}$$

Where  is the hidden state of the forward and  is the hidden state of the backward GRU layers. denotes the concatenation operation that combines both directional outputs into a single feature representation.

**Data preparation**

The well data used in this study were obtained from the open source SEG Wiki in LAS format. The data comes from a single well (Well 1), which serves as a training dataset. The well logs used include checkshot (CHKS), shear wave velocity (Vs), density (RHOB), gamma ray (GR), compression wave velocity (Vp), neutron porosity (NPHI), and water saturation (SW). The log data cover a depth interval of approximately 3300-7000 ft, as shown in the curve plot in Figure 3.

Feature selection was performed to identify and retain the most relevant variables while eliminating redundant or non-informative features. This process can improve model accuracy by reducing data complexity and minimizing the risk of overfitting (Zainuri et al., 2023).

The machine learning model depends on the quality of the data used. The presence of missing values and outliers can certainly affect the model performance. Therefore, statistical analysis of the dataset was conducted to ensure validity and reliability. The statistical characteristics of the well data are shown in Table 1.

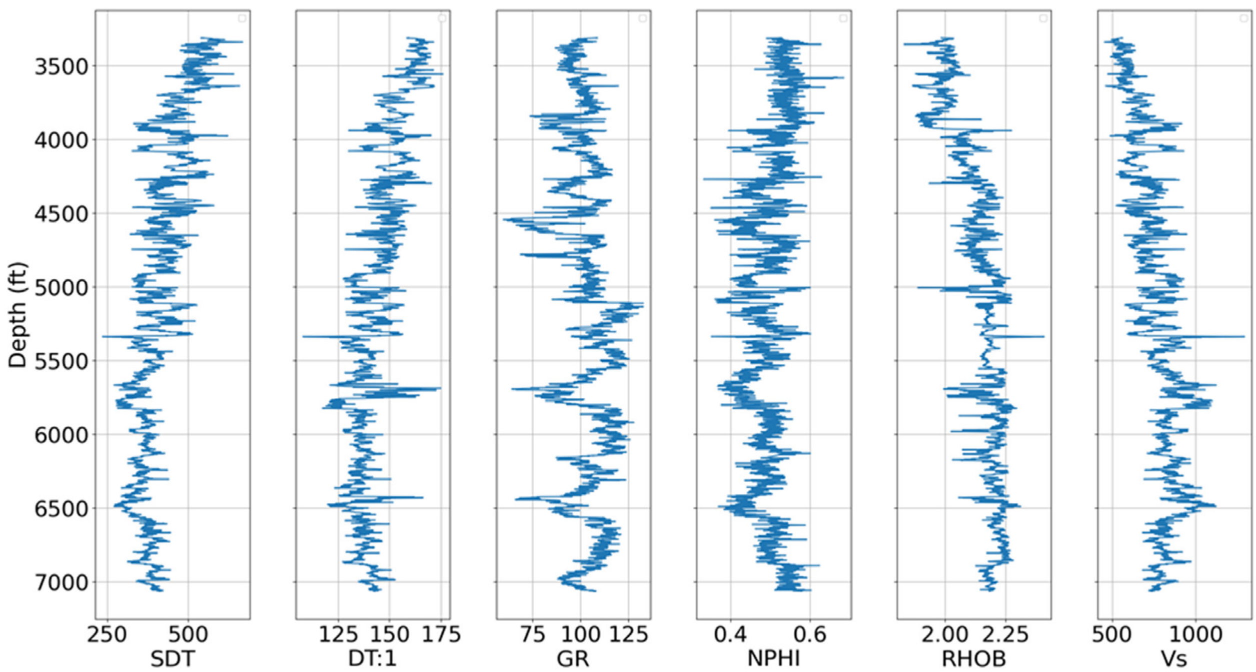


Figure 4. Plot Curve Well Log Data with shear wave travel time profile (SDT), compressional wave profile (DT:1), gamma ray profile (GR), neutron porosity profile (NPHI), shear wave velocity profile (Vs).

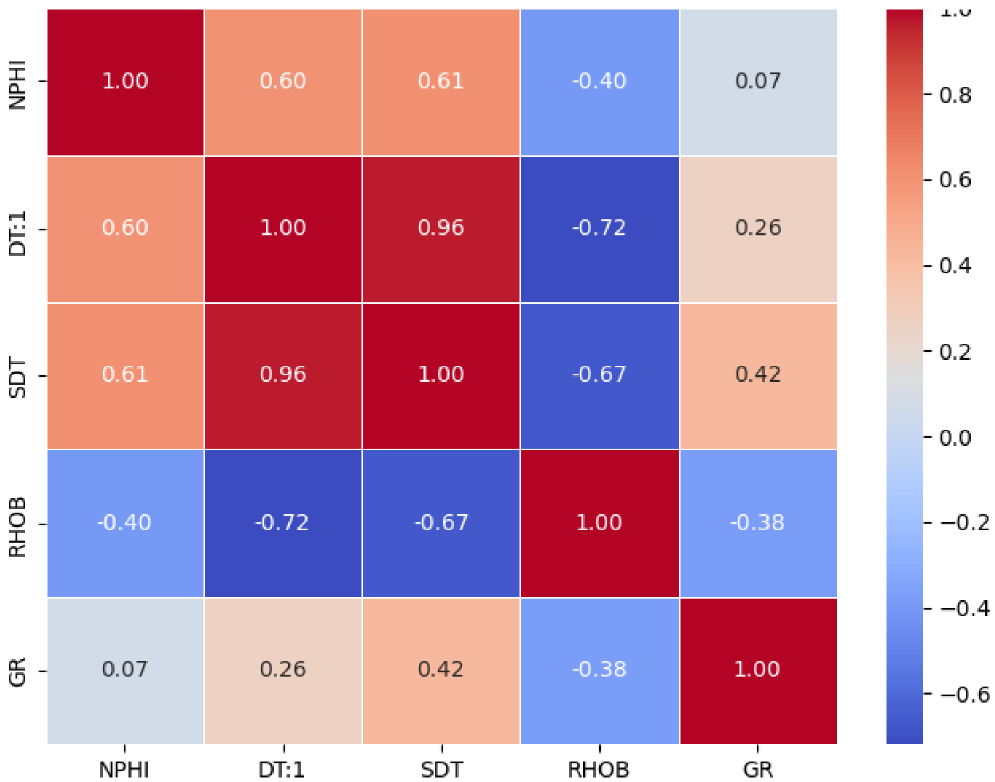


Figure 5. Correlation heatmap between log data (NPHI, DT, SDT, RHOB, GR). Colors indicate the strength and direction of correlation between parameters.

**Correlation analysis**

Correlation analysis is a statistical method used to identify collinear relationships among attributes in a dataset. This approach helps determine which variables provide significant information to the target parameter while disregarding less relevant attributes. Features with high correlation to the target tend to produce more accurate and reliable models. In this study, correlation analysis was applied to identify the most influential log features in predicting shear wave speed. The relationships between various log attributes and velocity of shear wave are visualized in Figure 5.

**Data normalization**

Before developing a machine learning model, it is essential to standardize the input data since different features may have varying scales and unit. Without normalization, the training process may become inefficient and fail to converge properly. The standardization formula used in this study is expressed as follows:

$$X_{scaled}^{ij} = \frac{X^{ij} - \mu_j}{\sigma_j} \tag{10}$$

where  is the standardized data result;  is original input data at i for feature j;  is the mean of feature j; and  is the standard deviation of feature j.

**Model evaluation**

In this study, the Adam optimization was employed to accelerate convergence during model training. Model performance was evaluated using two key metrics: Mean Absolute Error (MAE) and Coefficient of Determination ().

The MAE measures the average difference in the absolute value of the error between the actual and predicted data while  quantifies the proportion of variance in the observed data explained by the model. These are formulated as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(n_i - \overline{m}_i)^2}{\sum_{i=1}^{n}(m_i - \overline{m}_i)^2} \tag{11}$$

$$MAE = \frac{1}{x}\sum_{i=1}^{n}|m_i - n_i| \tag{12}$$

where $m_i$ is the measured value; $n_i$ is the estimated result; x is the sample size; and $\overline{m}_i$ is the average of the measured value. A good model is characterized by a high coefficient $R^2$ value, indicating a strong agreement between prodictions and actual data, and a low MAE value, indicating minimal prediction error. Figure 6 shows the workflow for predicting Vs using the GRU model based on well log data. The first step is to prepare the well log data, which includes elastic properties such as Vp, Vs, and density, as well as supporting logs such as neutron porosity and gamma ray separated into target data (Vs) and predictor data. Second, features with a good correlation with Vs are selected for input and data normalization is performed. Third, the data is divided into 60% training data and 40% test data. Fourth, the GRU model is built and parameters are selected (hyperparameter tuning). Fifth, the model results are evaluated using MAE; once the optimal model is obtained, testing is carried out on a new well (Well 2).

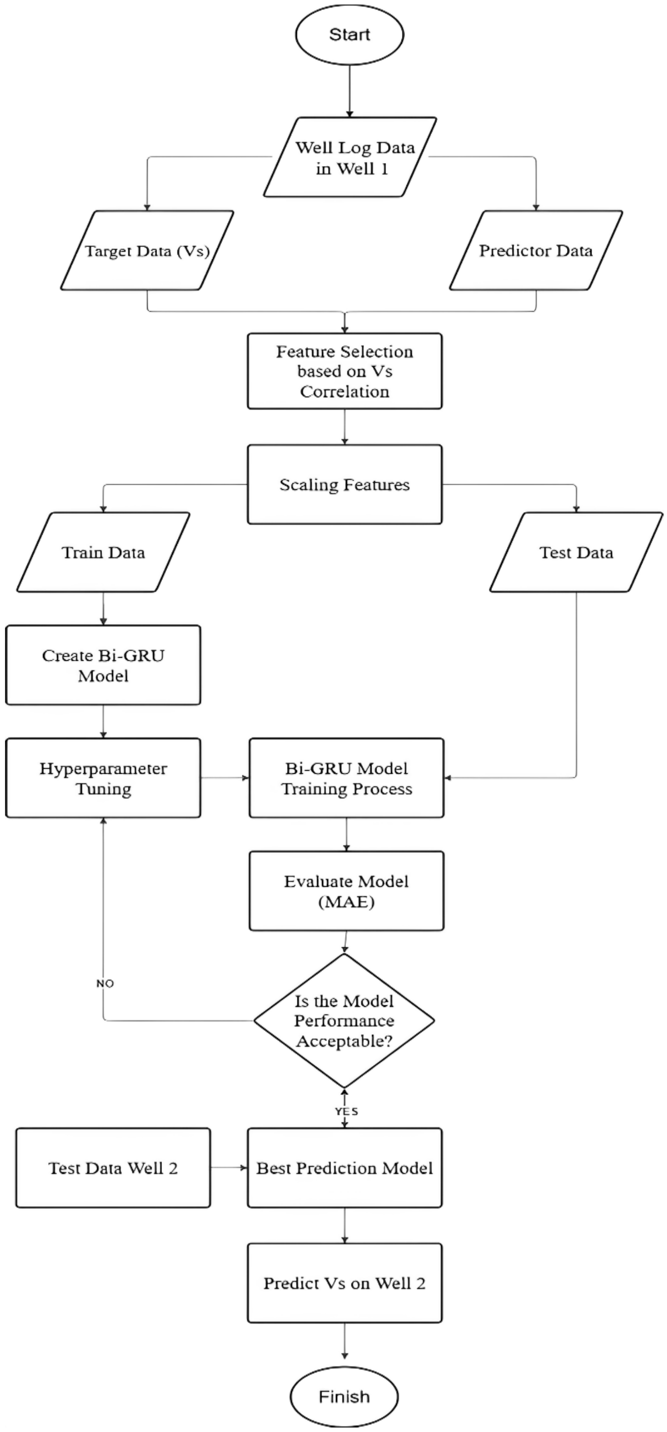


Figure 6. Workflow for predicting Vs using Bi-GRU model based on well log data.

## RESULT AND DISCUSSION

In the process of developing a machine learning model to predict shear wave velocity (S-wave velocity), selecting the right input features is an important step to improve model accuracy and understand the relationship among variables. In this study, the input features used in the machine learning model to predict log Vs consist of NPHI (Neutron Porosity Log), RHOB (Bulk Density Log), and GR (Gamma Ray Log). The selection of these features is based on the results of the correlation value of each feature against Vs. Figure 5 shows the correlation analysis of features such as NPHI, RHOB, DT, and GR against SDT, with correlation values of 0.61, -0.67, 0.96, and 0.42, respectively. The highest correlation is observed between DT and SDT. Theoretically and empirically, DT (Sonic Transit Time) or Vp (Compressional Wave Velocity) is known to have a strong correlation with Vs. However, in this study, it was attempted that these features were deliberately not included as model input, so that there were scenarios with and without Vp input. This approach was carried out to evaluate the extent to which other more commonly available elastic features in well log data can be used to accurately predict Vs values without relying on Vp. This strategy is also intended to simulate field conditions that are often encountered, where not all wells have complete Vp or DT data. Thus, if the model is able to produce fairly accurate Vs predictions using only Neutron porosity log (NPHI), Bulk density log (RHOB), and Gamma ray log (GR), this approach can be applied to wells without Vp data.

Predictions using the empirical Castagna method and multiple linear regression produced $R^2$ values of 0.6254 and 0.6017 (Figure 7). These results indicate that both methods have limited accuracy in predicting Vs. The empirical Castagna method has limitations because the lithology is not always uniform in each area, decreasing the accuracy. Meanwhile, the multiple linear regression method without inputting the compression wave velocity (Vp) produces a low correlation. This occurs because Vp has a strong linear relationship with Vs, thus, the absence of Vp as an input variable causes a significant decrease in model performance.

For machine learning prediction, hyperparameter tuning was conducted to determine the best model configuration. The parameters adjusted include the number of hidden layers, period, batch size, and learning rate. These parameters must be in accordance with the data used to avoid overfitting and underfitting. In this study, the machine learning methods used for Vs prediction are ANN and Bi-GRU. Several hyperparameter variations are carried out to obtain the best parameters in both methods.

Table 2. Scenarios for hyperparameter tuning in Well 1.

| No | Method | Parameter | | | | | $R^2$ (without Vp) | MAE (m/s) | $R^2$ (with Vp) | MAE (m/s) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Hidden layer | Batch Size | Epoch | Activation Function | Learning Rate | | | | |
| 1 | ANN | 4 | 64 | 500 | Relu | 0.005 | 0.8069 | 48.43 | 0.9692 | 16.89 |
| | Bi-GRU | 4 | 64 | 500 | Relu | 0.005 | 0.9630 | 13.07 | 0.9772 | 10.90 |
| 2 | ANN | 5 | 64 | 500 | Relu | 0.005 | 0.8545 | 45.74 | 0.9761 | 17.9 |
| | Bi-GRU | 5 | 64 | 500 | Relu | 0.005 | 0.9787 | 9.36 | 0.9868 | 11.22 |
| 3 | ANN | 6 | 128 | 500 | Relu | 0.005 | 0.8164 | 47.69 | 0.9697 | 17.65 |
| | Bi-GRU | 6 | 128 | 500 | Relu | 0.005 | 0.9678 | 11.26 | 0.9658 | 16.76 |
| 4 | ANN | 7 | 128 | 500 | Relu | 0.005 | 0.7904 | 49.41 | 0.9619 | 15.87 |
| | Bi-GRU | 7 | 128 | 500 | Relu | 0.005 | 0.9520 | 13.12 | 0.9732 | 11.42 |
| 5 | Castagna | | | | | | | | 0.6017 | 78.44 |
| 6 | MLR | | | | | | | | 0.6254 | 66.99 |

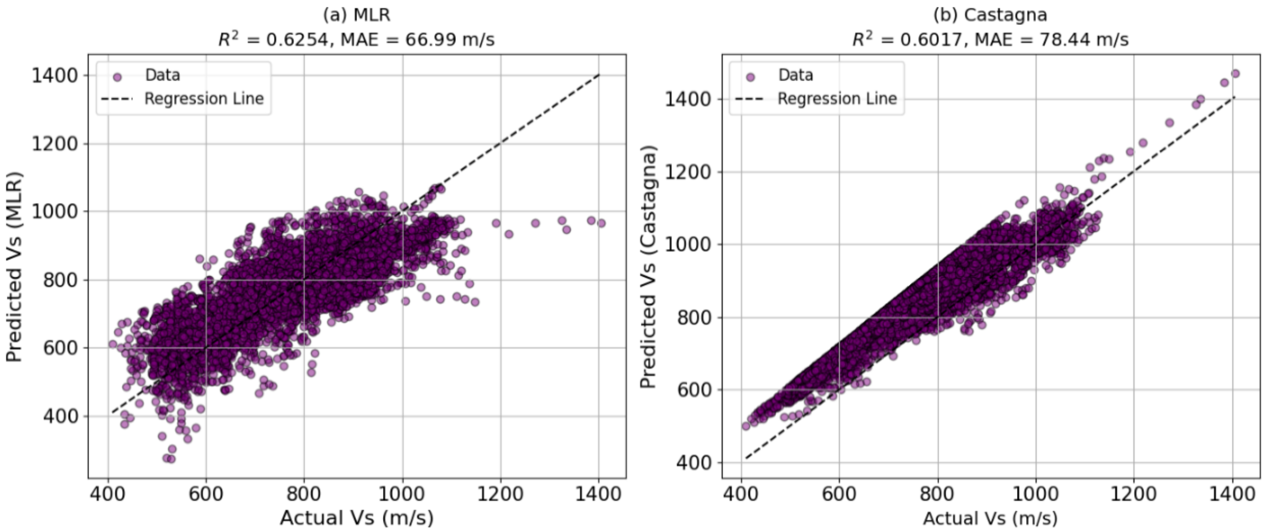


Figure 7. The results between actual Vs and predicted results using the (a) Multiple Linear Regression (MLR) method and (b) Castagna equation. The scatter plots show that both methods exhibit moderate correlation, with MLR providing slightly higher accuracy ($R^2$ = 0.6254, MAE = 66.99 m/s) compared to the Castagna equation ($R^2$ = 0.6017, MAE = 78.44 m/s).

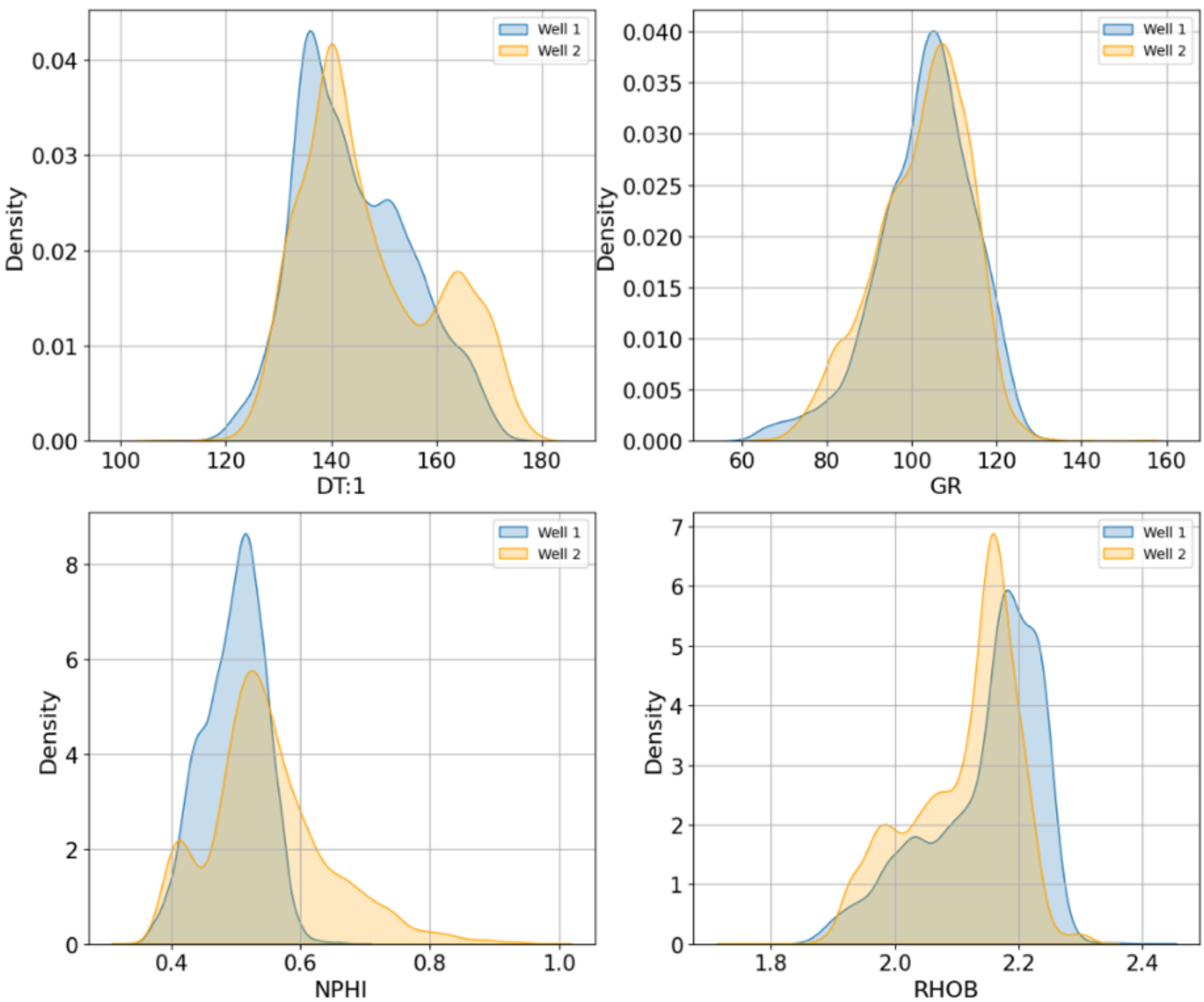


Figure 8. Data distribution of Well 1 and Well 2. The plots show the probability density of selected well log parameters (DT, GR, NPHI, and RHOB), indicating similar overall trends with slight variations in magnitude and spread between the two wells.

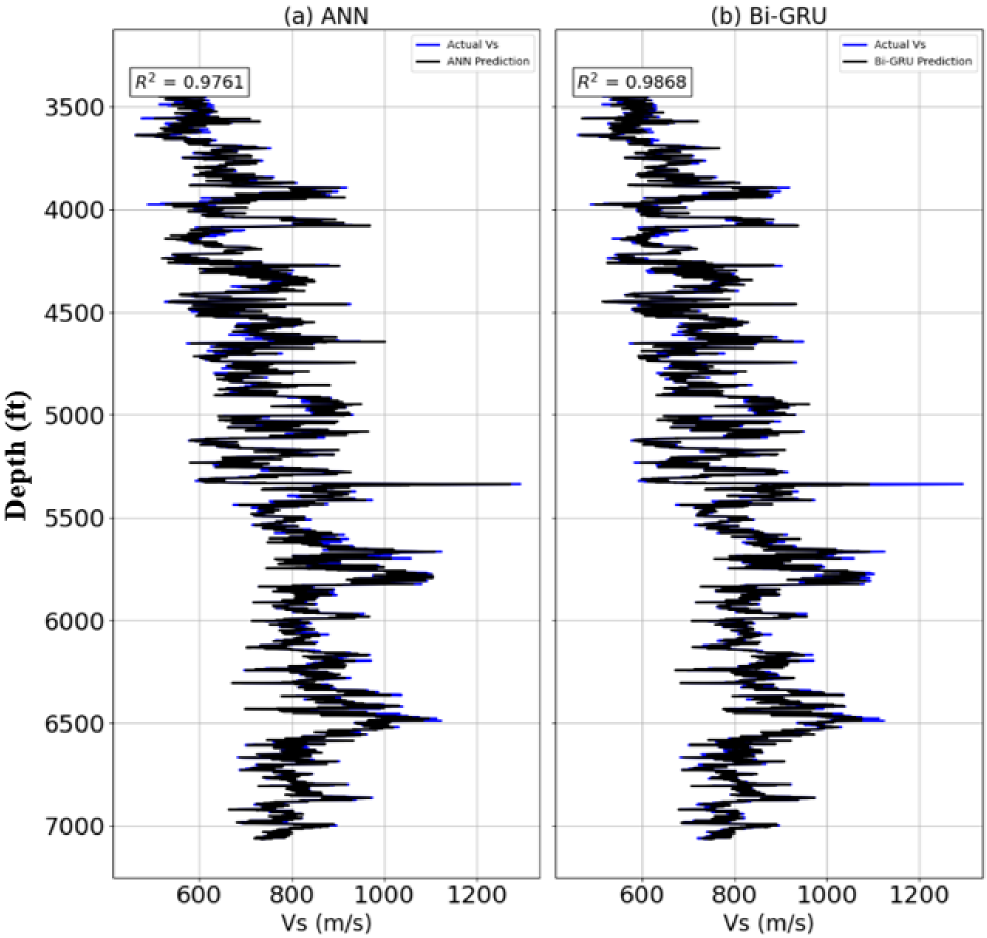


Figure 9. Plot Curves Actual vs Prediction Shear Wave with Vp input (a) ANN, (b) Bi-GRU.

Several scenarios are carried out to obtain a good scenario as in Table 2. Table 2 shows that the Bi-GRU model outperforms the ANN in all scenarios, both when using the input of the Vp and without Vp. This can be seen from the value of the determination coefficient $R^2$ which is consistently higher in each Bi-GRU configuration. In addition, increasing the number of hidden layers indicates that the Bi-GRU model is more stable and has better generalization capabilities than ANN.

In contrast, the performance of ANN does not increase significantly with addition of hidden layers, and even tends to fluctuate, indicating the possibility of overfitting or architectural limitations. Adding the Vp attribute to the model input has a significant positive impact on the performance of both types of models. For each configuration, the $R^2$ value increases consistently when Vp is used, and the MAE decreases drastically. For example, the ANN with 4 hidden layers has an $R^2$ of 0.8069 without Vp and increases to 0.9692 with Vp, accompanied by a decrease in MAE from 48.43 m/s to 16.89 m/s. The best performance of the Bi-GRU method is achieved in scenario 2 (Table. 2), with five hidden layers, a batch size of 64, and a learning rate of 0.005, with an $R^2$ value reaching 0.9787 without Vp and 0.9868 when using Vp, as well as a very low MAE (9.36 m/s and 11.22 m/s). This hyperparameter configuration is proven to provide the most optimal Bi-GRU prediction results in estimating shear wave velocity (Vs).

For comparison, the empirical Castagna method for sandstone produced an $R^2$ of 0.6017 and an MAE of 78.44 m/s, while MLR yields an an $R^2$ of 0.6254 and an MAE of 66.99 m/s. These results are considerably lower than those obtained using machine learning, confirming that data-driven models such as Bi-GRU and ANN are far superior in capturing the complexity of the non-linear relationship between well log data and Vs, compared to traditional linear models such as MLR and Castagna. Overall, deep learning-based models, especially Bi-GRU, demonstrate significant advantages in predicting shear wave velocity (Vs). The Bi-GRU architecture, capable of processing information bidirectionally forward and backward, enables a better understanding of sequential context compared to the ANN model. Although the ANN model is quite effective, it has limitations in handling data complexity and generalization capabilities. A comparison of the Vs prediction results by the two

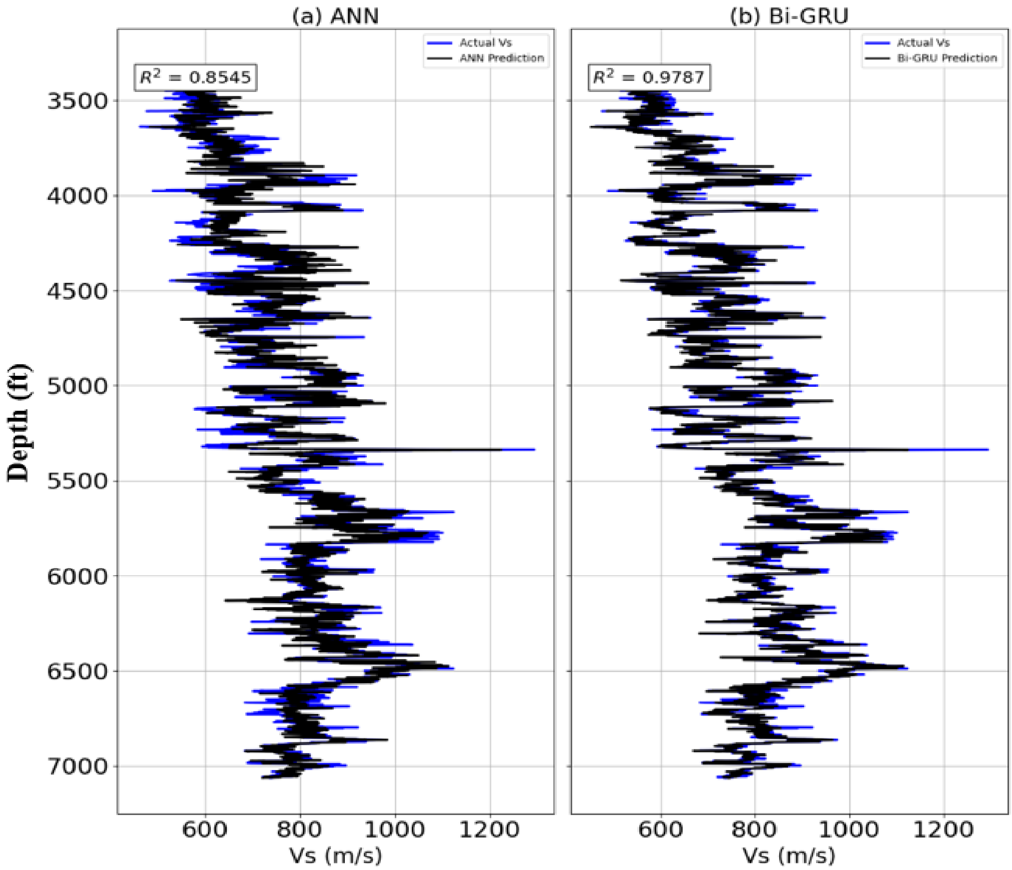


Figure 10. Plot Curves Actual vs Prediction Shear Wave without Vp input (a) ANN, (b) Bi-GRU.

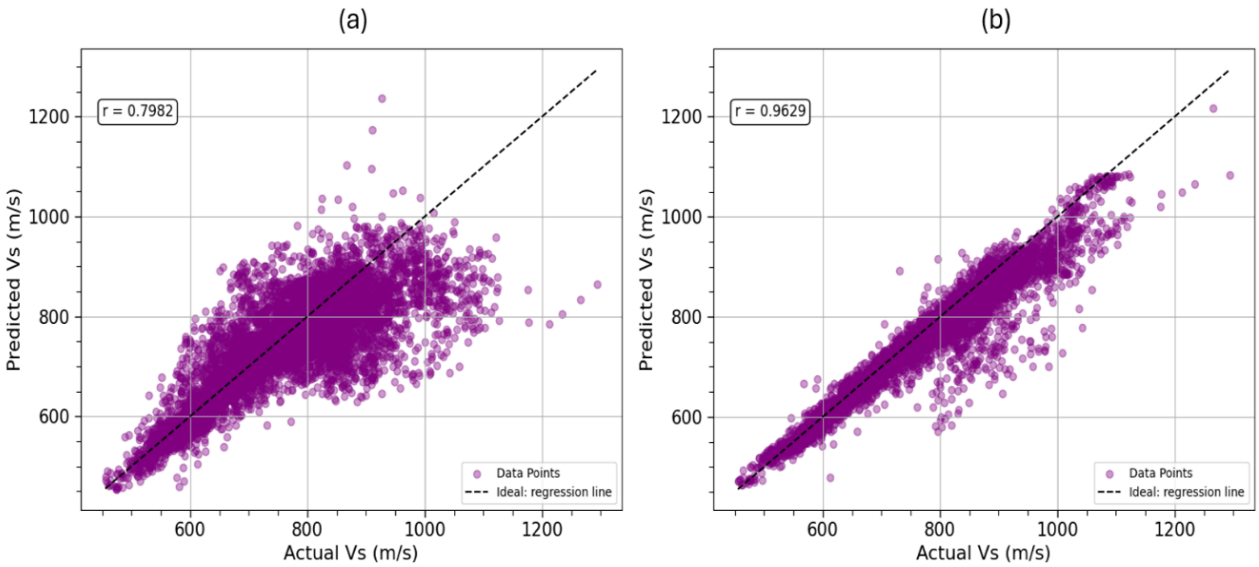


Figure 11. Scatter plot of Vs prediction results on Well 2 using the Bi-GRU model. Subplot (a) shows the results without Vp input (r = 0.7982), while subplot (b) shows the results with Vp input (r = 0.9629). The inclusion of Vp significantly improves the correlation and prediction accuracy, indicating that compressional velocity contributes valuable information for estimating shear wave velocity.

models, both with Vp input and without Vp, is shown in Figure Figure 9 and Figure 10.

Figure 11 shows the prediction results of the Bi-GRU model developed and trained using data from Well 1, then tested to predict the shear wave velocity (Vs) in Well 2. The distribution of data from each well can be seen in Figure 8. The model produces a correlation coefficient value of 0.9548 with Vp input, and 0.7982 without Vp input. These results indicate that the model has a fairly good generalization ability to data from other wells that are not used in the training process, even though there are differences in geological or lithological conditions between wells. Overall, the findings indicate that the Bi-GRU model is quite robust and has a strong potential to serve as a basis for Vs prediction in a wider area, while still acknowledging the inherent limitations of inter-well generalization.

## CONCLUSION

The prediction results of shear wave velocity (Vs) from various hyperparameter tuning scenarios show that the Bi-GRU machine learning method outperforms conventional methods, such as ANN, Castagna's empirical method for sandstone, and multiple linear regression. The superiority of Bi-GRU is reflected in the higher coefficient of determination ($R^2$) value and the lower mean absolute error (MAE) value. Specifically, the $R^2$ value obtained reaches 0.9787 without using Vp and increases to 0.9868 when Vp is used as input, with MAE of 9.36 m/s and 11.22 m/s, respectively. This shows that Bi-GRU has good stability and generalization capabilities, both in scenarios with and without Vp input.

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## GLOSSARY OF TERMS

| Symbol | Definition | Unit |
|---|---|---|
| Vp | Velocity of P-wave | m/s |
| RHOB | Rock's Bulk Density | g/cc |
| NPHI | Neutron Porosity | % |
| GR | Gamma Ray | API |
| DT | Compressional Slowness | us/ft |
| SDT | Shear Slowness | us/ft |
| GRU | Gate Recurrent unit | |
| ANN | Artificial Neural Network | |

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