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Lithological Facies Classification Using Attention-Based Gated Recurrent Unit

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Abstract: Lithological facies classification is a pivotal task in petroleum geology, underpinning reservoir characterization and influencing decision-making in exploration and production operations. Traditional classification methods, such as support vector machines and Gaussian process classifiers, often struggle with the complexity and nonlinearity of geological data, leading to suboptimal performance. Moreover, numerous prevalent approaches fail to adequately consider the inherent dependencies in the sequence of measurements from adjacent depths in a well. A novel approach leveraging an attention-based gated recurrent unit (AGRU) model is introduced in this paper to address these challenges. The AGRU model excels by exploiting the sequential nature of well-log data and capturing long-range dependencies through an attention mechanism. This model enables a flexible and context-dependent weighting of different parts of the sequence, enhancing the discernment of key features for classification. The proposed method was validated on two publicly available datasets. Results demonstrate a considerably improvement over traditional methods. Specifically, the AGRU model achieved superior performance metrics considering precision, recall, and F1-score.

Key words: facies classification; attention mechanism; GRU; MLP (multilayer perceptron)

1 Introduction

Lithological facies classification constitutes a fundamental component of petroleum geology, sedimentology, and reservoir engineering. This classification refers to the systematic categorization of rocks based on observable physical attributes, geophysical log measurements, and other related properties. Effective classification is pivotal for interpreting subsurface geological structures, demarcating reservoir zones, assessing hydrocarbon potential, and optimizing the process of oil and gas exploration and production[1].

Traditionally, lithological facies classification is

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primarily a manual process involving meticulous scrutiny of well logs and core descriptions by geologists and petrophysicists. However, with the advancement of data collection technologies, the volume, velocity, and variety of data have increased significantly[2, 3], resulting in increasingly challenging and error-prone manual analysis. Additionally, traditional interpretive methods often fail to capture subtle yet crucial patterns within high-dimensional geophysical datasets.

In response to these challenges, machine learning has been progressively adopted as a powerful tool for lithofacies classification, demonstrating its aptitude for handling complex, multidimensional datasets and its capacity to discern nuanced patterns unobservable through manual analysis[4]. Established machine learning models, such as support vector machine (SVM)[5], k-nearest neighbor (KNN)[6], random forest classifier (RFC)[7], and Gaussian process classifier (GPC)[8], have all been used with varying degrees of success in the domain of lithological facies classification. However, these models have limitations that constrain their effectiveness in lithological facies classification. Despite its efficiency for binary classification problems, the SVM model suffers from reduced effectiveness in multiclass classification scenarios and requires considerable computational power for large datasets. Regardless of its simplicity, the KNN algorithm exhibits sensitivity to the dimensionality and quality of data, often leading to suboptimal performance in the presence of irrelevant features or noise. RFC is powerful and robust; however, this model is prone to data overfitting if not carefully tuned and fails to capture temporal dependencies between data points, a characteristic often crucial for effective classification[9, 10, 11]. The GPC, while versatile, is computationally expensive for large datasets due to the necessity of inverting large covariance matrices.

An Attention-based Gated Recurrent Unit (AGRU) model is proposed for lithological facies classification to address these limitations. Gated recurrent unit (GRU)[12] networks have a unique memory cell structure that allows learning and remembering long-term dependencies in sequence data. This characteristic is particularly beneficial for classification due to the inherently sequential nature of the data obtained from well logs. Further enhancing the capabilities of GRU networks, the attention mechanism allows the model to learn and focus on the most relevant classification features. This mechanism is inspired by the human attention process and enables the GRU to assign different weights to various inputs at each time step, focusing on the features that are crucial for the task. By combining the strength of GRU in managing sequence data with the capability of the attention mechanism to discern the most important features, an attention-based GRU model can potentially provide superior facies classification. Overall, the summary of this paper is as follows.

- An innovative approach that employs a two-layer GRU is proposed to capture the influence of multiple features on lithofacies, thereby enhancing the performance of the classifier.
- The influence exerted by different features on lithofacies categories is also investigated. The attention mechanism is employed for assigning weights to these features to distinguish the varying degrees of influence among them effectively.
- Experiments on two public datasets are conducted, and the proposed model is compared with other widely used classification models. The experimental results confirm that the proposed model indeed outperforms the other models.

The remainder of this paper is organized as follows. Section 2 reviews work related to facies analysis. Section 3 presents the features and definitions widely used for facies classification, articulates the motivation for this study with specific examples, and introduces the problem definition and the GRU model used in this paper. Section 4 provides a detailed description of the proposed model, demonstrating its performance. Section 5 presents the experiments conducted using the proposed model on two datasets and the comparison of its performance with several classification models. The final section provides a brief summary of our work.

2 Related Work

Considering early lithofacies classification, the process was traditionally handled manually by specialists, which was prone to potential biases. Moreover, this manual classification approach is a considerably labor-intensive and time-consuming task when confronted with extensive datasets. Hence, the utilization of machine learning for lithofacies classification can result in substantial time savings and enhance classification efficiency[13].

Halotel et al.[14] successively applied the SVM and the random forest (RF) classifiers for lithofacies classification and compared the performances of the two models. The experimental results demonstrate that the RF classifier outperforms the SVM when considering classification performance. Ferreira et al.[15] applied k-means clustering to draw rock facies maps in unsupervised seismic facies classification methods for multi-attribute analysis. Mandal and Rezaee[16] implemented four distinct machine learning (ML) classification algorithms to predict lithofacies on the open dataset of the Panoma field located in the southwestern part of Kansas, USA. The four classification algorithms employed in this research are as follows: artificial neural networks (ANNs), SVM, decision trees, and GPC. Comparative experimental evidence reveals that ANN performs better on the validation dataset than the other classifiers. In addition, Son et al.[17] trained an ANN for lithofacies classification based on the relationship between lithofacies and other physical properties of rocks using core porosity data and partial interpretation results of lithofacies. This method also proves the high reliability of ANN.

The high dimensionality, nonlinear correlations, and overlapping feature spaces of lithofacies increase the suitability of nonparametric methods for handling complex datasets[18–22]. With the widespread application of deep learning[23–28], Imamverdiyev and Sukhostat[25] began to explore the use of deep learning for geological lithofacies classification in wells. They employed convolutional neural networks (CNNs) for feature extraction from multiple variables, resulting in improved classification results. Kakouei et al.[29] analyzed and compared the performance of five ANN methods to identify various structures in lithofacies and evaluated their capability compared to labor-intensive traditional methods. Numerous experiments proved that backpropagation neural networks can generate the most accurate results but failed to account for the cost required for the model. However, these methods mainly focus on feature extraction from variables, overlooking the internal associations among different features. Feng et al.[26] used a CNN within a Bayesian framework for lithofacies classification and applied variational methods to approximate the posterior distributions of the neural parameters, which are mathematically difficult to handle. dos Santos et al.[19] used bidirectional long short–term memory to recognize lithofacies types from well-logging curves automatically, thus enhancing lithology identification performance. Saleem et al.[21] used semi-supervised learning with pseudo-labeling for lithofacies analysis to leverage unlabeled data and overcome the scarcity of labeled data. Puzyrev and Elders[30] developed a deep convolutional autoencoder for unsupervised seismic lithofacies classification, eliminating the need for manually labeled examples. Considering the significant challenges that persist in 3D multiclass seismic lithofacies classification, Liu et al.[31] developed a supervised CNN and a semi-supervised generative adversarial network for 3D seismic lithofacies classification under abundant and limited well data conditions. Ippolito et al.[32] also used the method of combining supervised and unsupervised learning to improve phase prediction.

Numerous works have currently investigated lithofacies classification. However, the aforementioned studies have overlooked the influence of different features on lithofacies classification. Consequently, the use of the attention mechanism is proposed for weight distribution among different features, allocating relatively high weights to features with large influences. The GRU is employed to capture nonlinear features for lithofacies classification.

3 Preliminary

3.1 Feature definition

Several characteristics affect facies classification. Herein, the relevant features used in this paper are introduced, and a brief definition is provided.

- AC (Acoustic Travel Time): This feature is the time required for sound waves to pass through the rock, which can be used to evaluate its compactness and porosity.
- CAL (Caliper): This feature is the diameter of the wellbore recorded during well logging and is typically used to identify irregularities in the wellbore.
- GR (Gamma Ray): This characteristic is a measure of the gamma rays emitted by the rock and is typically used to assess its radioactivity. Thus, GR can be utilized to distinguish between clay rocks and other types of rocks.
- K (Conductivity): This feature is the conductivity of the rock and can be used to evaluate the water content and mineral composition of the rock.
- RD (Resistivity): This feature is the resistance of the rock to the passage of an electric current and is

typically used to assess rock porosity and water content.

- SP (Spontaneous Potential): This feature is the potential difference produced by chemical reactions between the rock and the surrounding fluid, which can be used to identify the presence of certain minerals and fluids.
- ILD_log10 (Log of Deep Induction Resistivity): This feature is a measure of resistivity at a considerable depth and can provide information regarding rock properties, such as porosity and water content.
- DeltaPHI (Difference between Neutron and Density Porosity): This feature is the difference in porosity calculated from neutron and density logs, which can assist in determining rock type and pore fluid.
- PHIND (Density Porosity): This characteristic involves the porosity evaluated by density logging, which can be used to assess the pore structure and water content of the rock.
- PE (Photoelectric Absorption): This feature measures the capability of rocks to absorb photon energy, which can be used to identify different mineral components.
- NM_M (Nonmarine or Marine Indicator): This indicator is used to label whether the rock originates from a nonmarine or marine environment.
- RELPOS (Relative Position): This feature represents the relative position of the sedimentary layer within its depositional cycle. Typically, 1 signifies the top of the depositional cycle, while 0 designates the base. RELPOS provides valuable insights into the formation processes of the strata.

Numerous parameters could influence lithological facies classification. The features utilized in the current study were not chosen randomly but on the basis of measurable real-world characteristics. For instance, in the Panoma field, the accessible features include “GR”, “ILD_log10”, “DeltaPHI”, “PHIND”, “PE”, “NM_M”, and “RELPOS”. By contrast, the Yanan field allows for features such as “AC”, “CAL”, “GR”, “K”, “RD”, and “SP”. The feature sets vary depending on the field, thereby highlighting the universality of the AGRU model. Specifically, this approach showcases the capability of the model to capture these nonlinear features comprehensively without restrictions imposed by the specifics of the feature selection.

Regarding rock categories, two distinct datasets have been selected, namely, those obtained specifically from the Panoma Field and the Yanan Oil Field. More precisely, the Panoma Field comprises nine facies: SS, CSiS, FSiS, SiSH, MS, WS, D, PS, and BS. Meanwhile, the Yan’an oil field encompasses seven facies: CS, ME, FI, SI, DO, LI, and MU. The abbreviations for each facies and their corresponding full names have been summarized in Table 1.

3.2 Motivation

A specific instance derived from a dataset of the Panoma field, North America[33]. The dataset comprises well-logging data from nine wells. Facies classification necessitates the selection of pertinent features. Therefore, GR, ILD_log10, PE, DeltaPHI, PHIND, NM_M, and RELPOS are selected in this study. In Fig. 1, four out of the nine wells are randomly selected, demonstrating a schematic representation of the aforementioned feature variations with depth. Additionally, the corresponding facies categories (i.e., SS, CSiS, FSiS, SiSH, MS, WS, D, PS, and BS) of different features are depicted in Fig. 1.

First, the well is named “SHRIMPLIN”. The results revealed that the seven feature data points of this well exhibit irregular variations with depth, increasing the difficulty of capturing the change patterns of corresponding facies. Simple classification models often struggle to achieve effective classification from multidimensional features. The second well, “SHANKLE”, shows variation patterns relatively similar to the first well. However, the multidimensional feature changes still present nonlinear variations. The

Table 1 Features and their abbreviations.

Dataset	Class of rocks	Abbreviation
Panoma	Nonmarine sandstone	SS
	Nonmarine coarse siltstone	CSiS
	Nonmarine fine siltstone	FSiS
	Marine siltstone and shale	SiSH
	Mudstone (limestone)	MS
	Wackestone (limestone)	WS
	Dolomite	D
	Packstone-grainstone (limestone)	PS
	Phylloid-algal bafflestone (limestone)	BS
Yanan	Coarse sandstone	CS
	Medium sandstone	ME
	Fine sandstone	FI
	Siltstone	SI
	Dolomite	DO
	Limestone	LI
	Mudstone	MU

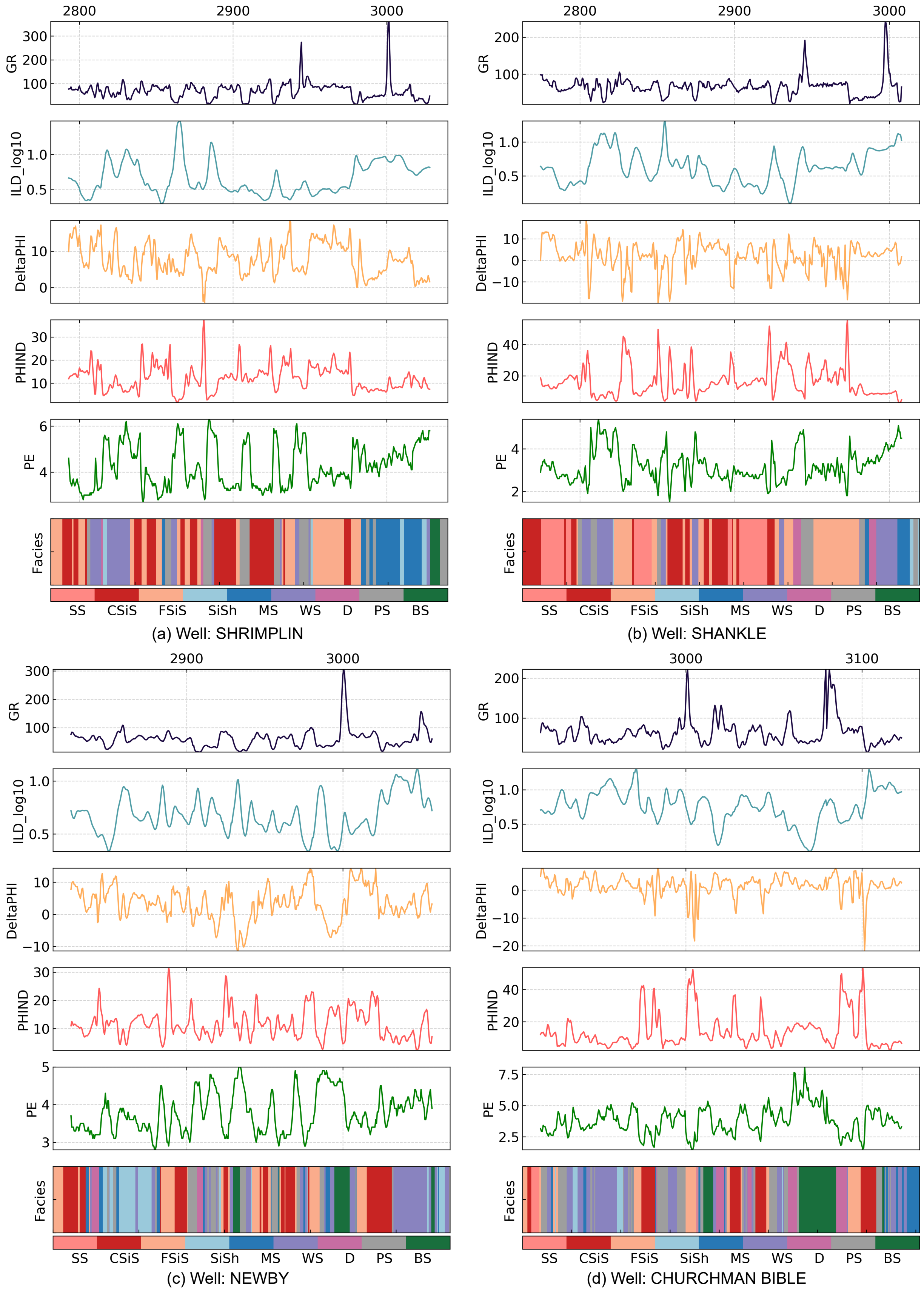

Fig. 1 Variation of rock features with depth in different wells.

variation patterns of the third and fourth wells may not resemble those of the first well but still remain irregular. Hence, identifying the degree of influence of different features on facies categories from multidimensional features, thereby achieving high-precision facies classification, is crucial.

3.3 Problem definition

For the Panoma field, each core sample in well logging is defined as a 9-tuple $c_d = (\mathrm{SS}_d, \mathrm{CSiS}_d, \mathrm{FSiS}_d, \mathrm{SiSH}_d, \mathrm{MS}_d, \mathrm{WS}_d, \mathrm{D}_d, \mathrm{PS}_d, \mathrm{BS}_d)$, which represents the overall characteristics of that core. For the Yanan oil field, each core sample in well logging is defined as a 7-tuple $c_d = (\mathrm{CS}_d, \mathrm{ME}_d, \mathrm{FI}_d, \mathrm{SI}_d, \mathrm{DO}_d, \mathrm{LI}_d, \mathrm{MU}_d)$. With the variation in depth, the changes in the cores within each oil field can be expressed as a sequence $C = \{c_1, c_2, \ldots, c_d\}$. Finally, this study aims to predict the types of lithofacies based on the obtainable features of rocks.

3.4 Gated recurrent unit

The GRU[34] is a type of recurrent neural network (RNN) unit designed for processing sequence data, and the basic framework of the GRU is shown in Fig. 2. Allowing the network to learn long-term dependencies effectively helps alleviate the vanishing and exploding gradient problems in RNNs. Compared to long short-term memory (LSTM), which is another popular RNN unit, the GRU has a simple structure. LSTM has only two gates: the update gate and the reset gate.

Update gate: This gate determines which information will be carried forward to the new hidden state. The function of the update gate is similar to the combined role of the forget and input gates in the LSTM. Specifically, the operations of a GRU can be described with the following formulas:

$$z_d = \sigma(w_z \cdot x + b_z) \tag{1}$$

Where x is denoted as the input of GRU, w_z is the weight matrix corresponding to the update gate, b_z is the bias of the update gate, and σ is the sigmoid activation function.

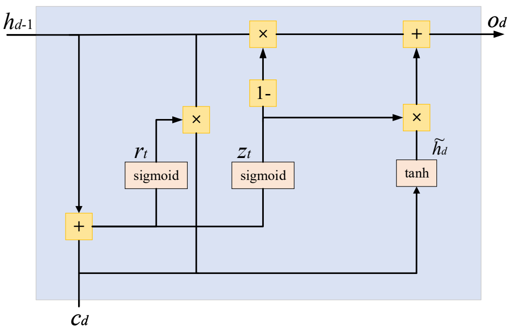

Fig. 2 Architecture of GRU.

Reset gate: This gate determines how to combine the combination of the new input with the past hidden state to produce a candidate hidden state.

$$r_d = \sigma(w_r \cdot x + b_r) \tag{2}$$

Similarly, w_r is the weight matrix corresponding to the reset gate, and b_r is the bias of the reset gate.

The candidate hidden state can be expressed as follows:

$$\tilde{h}_d = \tanh\left(w_{\tilde{h}} \cdot [r_d \odot x]\right) \tag{3}$$

where tanh represents the hyperbolic tangent function, $\odot$ represents element-wise multiplication (Hadamard product), and $[r_d \odot x]$ represents concatenating r_d and x along a particular axis.

The final hidden state can be expressed as

$$h_d = (1 - z_d) \odot h_{d-1} + z_d \odot \tilde{h}_d \tag{4}$$

Overall, by introducing gating mechanisms, GRUs allow models to decide when to update or forget their hidden states, thus effectively capturing long-term dependencies when processing sequence data.

4 Proposed Model

This paper aims to present an innovative approach to lithofacies classification using an attention-based GRU model. The capability of the model to address the limitations of traditional ML techniques while providing precise and reliable results will be demonstrated. The framework of AGRU is shown in Fig. 3. First, the detectable features of rocks are extracted, and then feature vectors can be obtained. The feature vectors are inputted into the two-layer GRU model in depth order for training, and then the attention layer is used to assign their weights. Finally, the output results of the attention layer are fed into the MLP for training to obtain the final classification results. The specific details are introduced below. First, the lithology changes across depths in different wells are treated as separate sequences. Each sequence of lithology changes is then fed into the GRU model. Herein, the input X of the model is defined as

$$X = \begin{bmatrix} h_{d-1} \\ c_d \end{bmatrix} \tag{5}$$

where h_{d-1} is the hidden layer state corresponding to $d-1$ depth, and c_d is the current rock feature sequence.

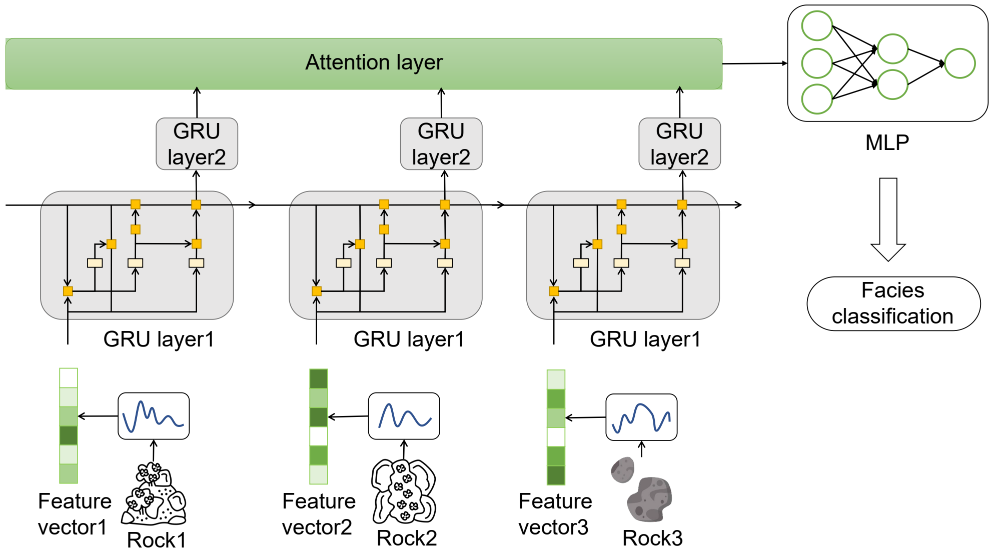

Fig. 3 Architecture of AGRU.

Given the sequential order of the rock features, the GRU is highly efficient in capturing the the nonlinear dependencies within the data. Thus, the GRU can understand and learn from the dynamic interactions among rock characteristics that occur at different depths, which are often overlooked by traditional ML models.

The update gate performs the initial analysis of the input feature sequence. This gate learns to discern and filter out the unimportant rock features in the sequence while selectively memorizing the crucial rock information. This critical information is then transferred to the new hidden state of the GRU after processing by the update gate. This gate effectively provides the model with a mechanism for focusing on significant information and ignoring redundant or less relevant details.

$$z_d = \sigma(W_z \cdot X + B_z) \tag{6}$$

where X is the input of AGRU, W_z is the weight matrix corresponding to the update gate of AGRU, and B_z is the bias of the update gate.

By contrast, the reset gate decides the combination of the newly memorized information with the previous hidden state to generate a new candidate hidden state. The reset gate serves to balance the influence of the new input and the historical information carried by the hidden state. The operation of this gate provides the GRU model with its extraordinary capability to capture long-term dependencies within the sequence.

$$r_d = \sigma(W_r \cdot X + B_r) \tag{7}$$

Similarly, W_r as the weight matrix corresponds to the reset gate, B_r as the bias of the reset gate. Candidate hidden layer states $\tilde{h}_d$ and the final output can then be generated as follows:

$$\tilde{h}_d = \tanh\left(W_{\tilde{h}} \cdot [r_d \odot X]\right) \tag{8}$$

$$h_d = (1 - z_d) \odot h_{d-1} + z_d \odot \tilde{h}_d \tag{9}$$

Currently, the output of GRU can be denoted as follows:

$$o_{d+1,c_d} = (W_h h_d)^{\mathrm{T}} (W_X c_d) \tag{10}$$

Thus, the proposed approach can effectively analyze the depth-ordered sequence of rock features from each well by employing a GRU model. This approach leverages the unique capabilities of the GRU model to focus on important details, filter out noise, and capture long-term dependencies within the sequence. This phenomenon results in a powerful model that can accurately predict lithology classes from depthwise rock feature sequences.

Coupling the GRU model with an attention mechanism is proposed to focus on the sequence information in the changes in lithological characteristics. This enhanced model aims to provide a means for the GRU to focus selectively on crucial rock information during the classification task. The attention mechanism is an advanced technique that assigns different weights to various parts of the input sequence. The model can focus on the most relevant pieces of information and less on the slightly relevant ones. This selective attention capability significantly enhances the capability of the model to extract useful information from sequences of rock features.

In the AGRU model, the attention mechanism is incorporated as an additional layer on top of the GRU layers. Considering lithology classification, the attention mechanism allows the model to assign varying degrees of relevance to different parts of the input sequence when making predictions. Such an assignment is performed by applying weights to different parts of the input, which are calculated using the attention formula. This attention layer is responsible for generating attention weights for each feature in the sequence. The GRU layer outputs a sequence of hidden states, each corresponding to a specific feature in the sequence. The attention layer takes these hidden states as input and computes an attention weight for each state:

$$p_d = \sum_{d=1}^{S} \alpha_d h_d \tag{11}$$

where α_d denotes the attention weight, which is calculated as follows:

$$\alpha_d = \text{softmax}(C_d) = \frac{\exp(C_d)}{\sum_{d=1}^{D} C_d} \tag{12}$$

These attention weights are then used to form a weighted sum of the hidden states, resulting in a context vector that effectively summarizes the input sequence with a focus on the most crucial features.

$$o_{d+1,c_d} = \left(W_p p_d\right)^{\mathrm{T}} (W_C c_d) \tag{13}$$

The attention layer uses a neural network to compute the attention weights. The inputs to this network are the hidden states of the GRU, and the output is a score for each state. These scores are then passed through a softmax function to convert them into attention weights, demonstrating a sum of 1 and allowing them to be interpreted as probabilities. The model provides additional "attention" to the corresponding feature when the attention weight of a hidden state is high. The model can concentrate on the features that are most indicative of the lithology class by using the attention mechanism while providing minimal attention to the less important or irrelevant features. This condition results in a highly accurate and robust classification. Overall, the enhanced model can selectively focus on the most crucial rock information, resulting in a highly accurate lithological facies classification.

Finally, the MLP network is used to obtain the final result of the lithofacies classification. MLPs are generally widely used in machine learning models due to their capability to learn and model nonlinear and complex relationships. An MLP comprises at least three layers of nodes: an input layer, a hidden layer, and an output layer. Each node in one layer connects with a certain weight to every node in the following layer. An MLP is employed in the final stage of prediction after the attention-based GRU layer. The MLP is instrumental in further refining the learned feature representations by the GRU, adding depth to the model, and enhancing prediction accuracy. Moreover, MLP helps learn high-level features based on the sequences processed by GRU, which are essential for the subsequent lithology classification.

5 Experiment

5.1 Datasets

In the experiments, two publicly available datasets, namely the Panoma field dataset from North America and the Yanan oil field dataset from China, are utilized. The Panoma field dataset includes information such as the types of facies, well names, well depth, and features (including GR, ILD_log10, DeltaPHI, PHIND, PE, NM_M, and RELPOS). The Yanan oil field dataset includes information such as the types of facies and features (AC, CAL, GR, K, RD, and SP). A scatter plot is used to visualize the relationships between multiple variables in the Panoma dataset effectively, as shown in each row and column in Fig. 4 represents a variable, while the horizontal and vertical coordinates of each small graph correspond to the variables of its columns and rows, respectively. Thus, the relationship between multiple variables can be simultaneously observed in Fig. 4.

5.2 Baselines

This section provides brief introductions to four commonly utilized baseline models in facies classification: SVM[5], GPC[7], RNN[35], and LSTM[36]. SVMs excel in high-dimensional spaces by constructing an optimal hyperplane for classification. They are used in facies classification for handling complex geological data with numerous features. However, the primary drawback of SVM lies in its sensitivity to noise and its tendency to perform poorly when the classes are heavily overlapping. GPC models nonlinear relationships effectively and provides a

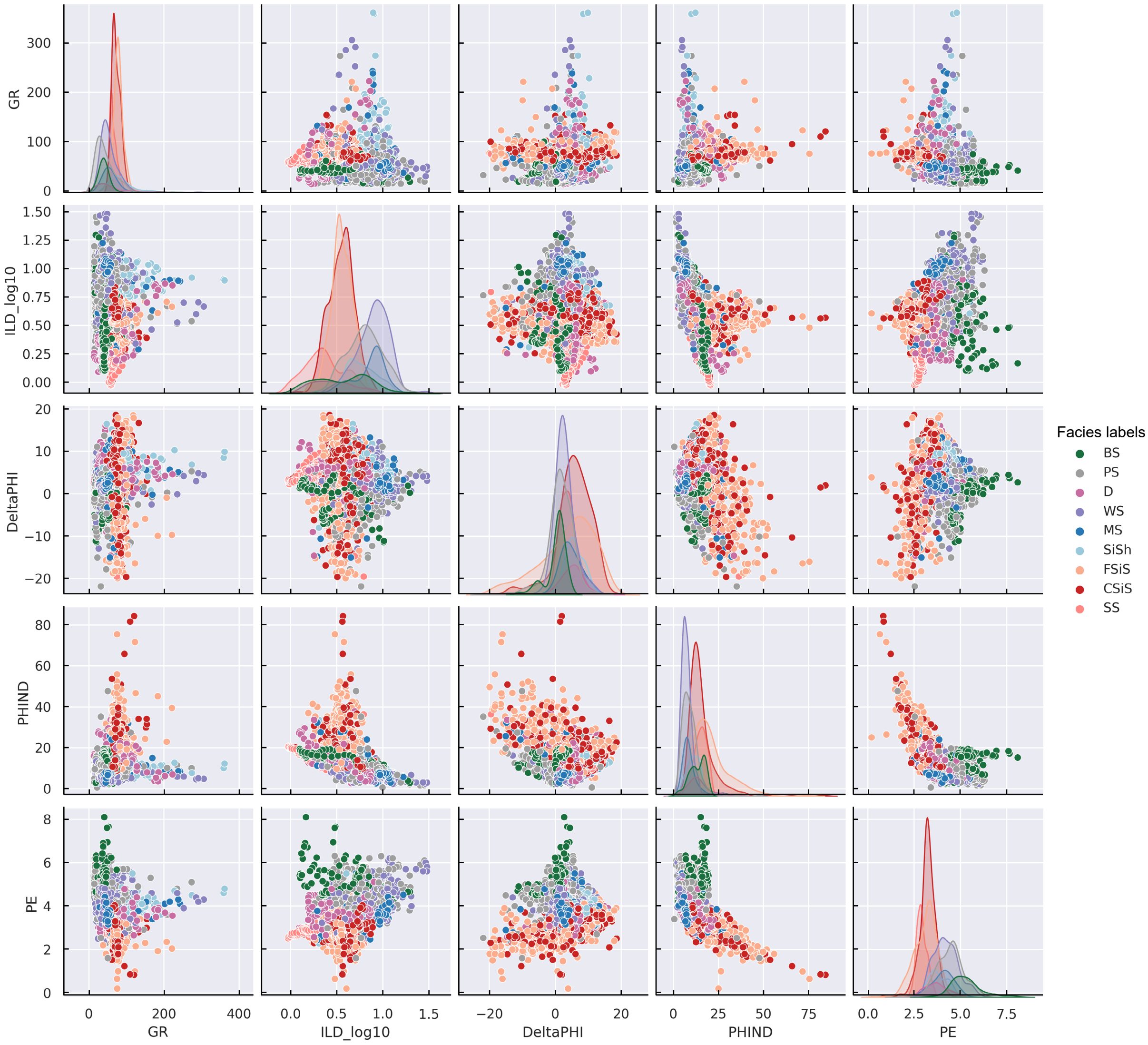

Fig. 4 Relationship between multiple variables in Panoma.

measure of uncertainty for risk assessment in facies classification. However, GPCs can be computationally expensive and might be unsuitable for very large datasets. The functions of RNN and LSTM are similar to those of GRU, but RNN is prone to problems of gradient vanishing and explosion. LSTM has a longer training time than GRU due to the complex gate structure.

5.3 Evaluation metrics

In the study of facies classification, evaluating the performance of the proposed models comprehensively is crucial. Therefore, several widely recognized metrics have been adopted to assess the effectiveness of the models. These metrics include precision, recall, and F1-score.

Precision gauges the accuracy of the predictions. Precision measures the proportion of ture positives out of all the positive predictions. High precision indicates that the model makes few false-positive errors.

Recall, also known as sensitivity, measures the proportion of actual positives that are correctly identified. High recall rate implies implies the model has a low false-negative rate.

The F1-score is a harmonic mean of precision and recall. This metric is particularly useful when the data distribution is uneven because it considers false positives and negatives. The F1-score offers a balanced perspective on the model's performance, particularly when the cost of false positives and negatives is significantly different.

These metrics were computed in the experiments for all the models to provide a comprehensive view of their performance. Therefore, well-informed conclusions regarding the suitability of these models for facies classification were drawn.

5.4 Performance comparison

A comparative analysis of multiple models aimed at rock phase classification (Fig. 5), specifically SVM, GPC, RNN, LSTM, and AGRU, is conducted in this paper. The performance of the model is evaluated using precision, recall, and F1-score on two datasets, Panoma and Yanan.

The analysis revealed the superiority of the AGRU model across all evaluation metrics in both datasets, emphasizing its robustness and applicability to rock phase classification. The model provided precision, recall, and F1-score of 0.77, 0.76, and 0.76, respectively, for the Yanan dataset and 0.85, 0.81, and 0.81, respectively, for the Panoma dataset. These results highlight the benefits of applying attention mechanisms to GRUs, which effectively handle the temporal dependencies in the data.

Comparatively, SVM achieved commendable performance on the Yanan dataset, with precision, recall, and F1-score of 0.75, 0.74, and 0.75, respectively, but struggled on the Panoma dataset (0.66, 0.65, and 0.63, respectively). Despite demonstrating improvement over RNN and being comparable to AGRU on the Yanan dataset (0.84, 0.81, and 0.80), the LSTM model was not as efficient on the Panoma dataset. This variance in performance could be attributed to the capacity of the LSTM model to learn and remember over long sequences, which may have been highly suited to the Yanan dataset.

The attention mechanism in the AGRU model enables it to focus on the most important aspects of the input sequence, reducing the effect of noise and less relevant features. This adaptability endows it with an advantage over traditional LSTM and RNN architectures, as shown in the high scores across the datasets.

Overall, the results indicate that attention mechanisms, particularly when applied to GRUs, can significantly enhance rock phase classification. Future work could investigate further improvements, such as combining attention mechanisms with other models or applying advanced regularization techniques. Despite the challenges involved in this classification task, the proposed AGRU model exhibits extensive application potential in the field of geology and related applications.

5.5 Parameter selection

GRU layer: The model was tested with GRU layers set to 1, 2, and 3. The impact of varying the number of GRU layers on model performance is demonstrated in Fig. 6. The results indicated that a single layer might be insufficient for the model to express the complexity of the problem adequately, leading to suboptimal performance. The performance of the model significantly improved with two layers. However, three layers led to a decrease in performance. Overly deep GRU layers can overcomplicate the model, increasing its susceptibility not only to overfitting but also to gradient vanishing or exploding issues, which results in an unstable training process.

Embedding dimension: Experiments were conducted with embedding dimensions set to 32, 64, and 128. Considering precision, recall, and F1-score, the resulting model performances on the Panoma and Yanan datasets are displayed in Fig. 7. Observations revealed optimal model performance when the embedding dimension was set to 64. A large dimension size can potentially increase the capability of the model

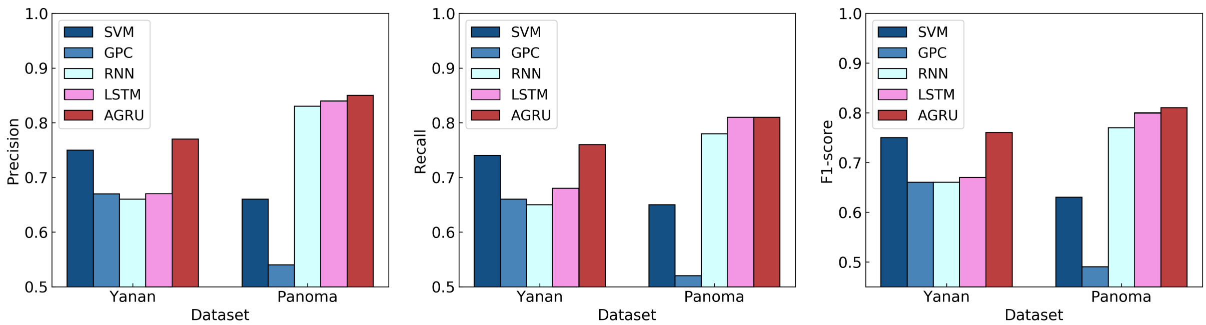

Fig. 5 Classification results of AGRU.

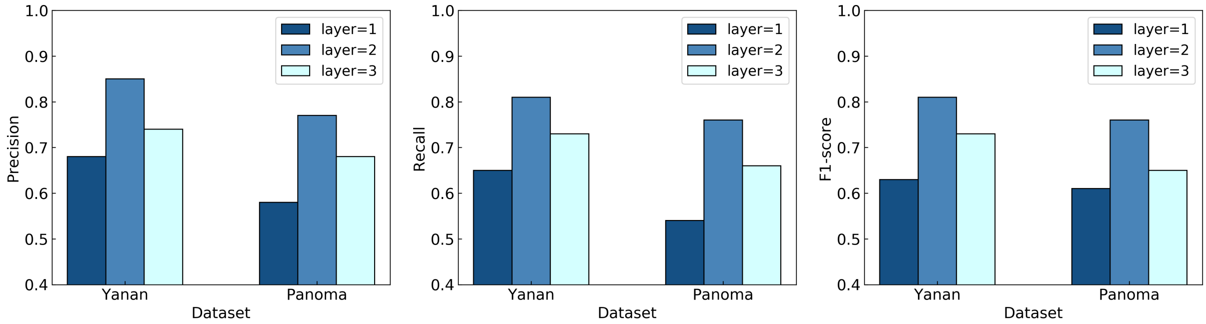

Fig. 6 Performance of AGRU models corresponding to different GRU layers.

to represent features; however, this condition may also introduce redundancy. Hence, 64 was determined to be a suitable dimension size.

Other Parameters: The epoch was set to 300, with a dropout rate of 0.5 and a batch size of 32. An early stopping strategy, where training would be halted if the model performance did not improve for 10 consecutive epochs (patience = 10), was used to prevent overfitting and unnecessary long training times.

6 Conclusion

Overall, this paper presents a novel and effective method for facies classification utilizing an AGRU model. The AGRU model effectively captured the inherent sequential nature and existing dependencies in well log data by leveraging the power of RNN and attention mechanisms. This approach considerably enhanced the discernment of key features, yielding higher accuracy in facies classification compared to traditional methods. The proposed method was rigorously validated on two publicly available datasets, Panoma and Yanan, where it significantly outperformed traditional and contemporary methods such as SVM, GPC, RNN, and LSTM. The method also delivered superior results considering precision, recall, and F1-score, demonstrating its effectiveness and robustness. Furthermore, the performance improvement introduced by the proposed model can lead to precise and reliable subsurface reservoir modeling, facilitating highly informed and effective decision-making processes in oil and gas exploration and production. This phenomenon could potentially have a substantial impact on operational efficiency and profitability within the industry.

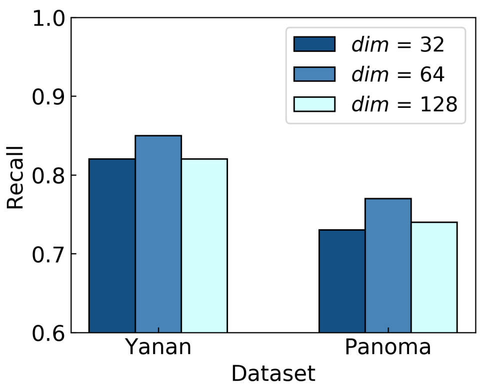

Fig. 7 Performance of AGRU models corresponding to different embedding dimensions.

Future work could extend the applicability of the AGRU model to other geological classification tasks, such as lithology or depositional environment classification. Additionally, integration with other data types, such as seismic or production data, could further enhance the performance of the model. This study aims to contribute to the broad adoption of advanced ML techniques considering petroleum geology and beyond.

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