Heliyon 9 (2023) e21913

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Prediction of geomechanical bearing capacity using autoregressive deep neural network in carbon capture and storage systems

Sulieman Ibraheem Shelash Al-Hawary [a], Eyhab Ali [b], Suhair Mohammad Husein Kamona [c], Luma Hussain Saleh [d], Alzahraa S. Abdulwahid [e], Dahlia N. Al-Saidi [f], Muataz S. Alhassan [g], Fadhil A. Rasen [h], Hussein Abdullah Abbas [i], Ahmed Alawadi [j,k,l], Ali Hashim Abbas [m], Mohammad Sina [n,*]

[a] Department of Business Administration, Business School, Al al-Bayt University, P.O.Box 130040, Mafraq, 25113, Jordan
[b] College of Chemistry, Al-Zahraa University for Women, Karbala, Iraq
[c] Department of Medical Laboratory Technics, Al-Manara College for Medical Sciences, Amarah, Iraq
[d] Department of Anesthesia Techniques, Al-Noor University College, Nineveh, Iraq
[e] Department of Medical Laboratory Technics, Al-Hadi University College, Baghdad, 10011, Iraq
[f] Department of Medical Laboratories Technology, AL-Nisour University College, Baghdad, Iraq
[g] Division of Advanced Nano Material Technologies, Scientific Research Center, Al-Ayen University, Thi-Qar, Iraq
[h] Department of Medical Engineering, Al-Esraa University College, Baghdad, Iraq
[i] College of Technical Engineering, National University of Science and Technology, Dhi Qar, Iraq
[j] College of Technical Engineering, The Islamic University, Najaf, Iraq
[k] College of Technical Engineering, The Islamic University of Al Diwaniyah, Iraq
[l] College of Technical Engineering, The Islamic University of Babylon, Iraq
[m] College of Technical Engineering, Imam Ja'afar Al-Sadiq University, Al-Muthanna, 66002, Iraq
[n] Department of Petroleum Engineering, Omidiyeh Branch, Islamic Azad University, Omidiyeh, Iran

ARTICLE INFO

Keywords:
Carbon capture and storage (CCS)
Machine learning
Shear wave velocity
Autoregressive deep neural network
Geomechanics
Petrophysics

ABSTRACT

Carbon Capture and Storage (CCS) field is growing rapidly as a means to mitigate the accumulation of greenhouse gas emissions. However, the geomechanical stability of CCS systems, particularly related to bearing capacity, remains a critical challenge that requires accurate prediction models. In this research paper, we investigate the efficacy of employing an Autoregressive Deep Neural Network (ARDNN) algorithm to predict the geomechanical bearing capacity in CCS systems through shear wave velocity prediction as an index for bearing capacity evaluation of deep rock formations. The model utilizes a dataset consisting of 23,000 data points to train and test the ARDNN algorithm. Its scalability, use of deep learning techniques, automatic feature extraction, adaptability to changes in data, and versatility in various prediction tasks make it an attractive option for accurate predictions. The results demonstrate exceptional performance, as evidenced by an R-squared value of 0.9906 and a mean squared error of 0.0438 for the test data compared to the measured data. This research has significant practical implications for effectively predicting geomechanical stability in CCS systems, thus mitigating potential risks associated with their operation.

* Corresponding author.
E-mail addresses: eyhabali@alzahraa.edu.iq (E. Ali), suhairmohammad@uomanara.edu.iq (S. Mohammad Husein Kamona), luma.hussain@alnoor.edu.iq (L. Hussain Saleh), mszahrasabah@huc.edu.iq (A.S. Abdulwahid), dahlia.n.path@nuc.edu.iq (D.N. Al-Saidi), muataz@alayen.edu.iq (M.S. Alhassan), fadhil-abd@esraa.edu.iq (F.A. Rasen), husseinalshuwaili593@gmail.com (H. Abdullah Abbas), ahmedalawadi85@gmail.com (A. Alawadi), alihashimalsalamy78@gmail.com (A.H. Abbas), m.sina00691@gmail.com (M. Sina).

https://doi.org/10.1016/j.heliyon.2023.e21913
Received 29 May 2023; Received in revised form 29 October 2023; Accepted 31 October 2023
Available online 7 November 2023

1. Introduction

Carbon capture and storage (CCS) has been identified as one of the effective ways of mitigating greenhouse gas emissions. The successful deployment of CCS involves the identification of safe and suitable storage locations while minimizing the risk of leakage [1]. The bearing capacity of storage rock against geomechanics/geotectonic stresses is one of the emerging concerns about safe storage in CCS candidate sites. Bearing capacity, on the other hand, refers to the ability of a soil or rock foundation to support loads from structures or other heavy equipment. In Carbon Capture and Storage (CCS) systems, this is important because the underground reservoirs used to store carbon dioxide must be able to support the pressure of the injected gas without collapsing or deforming. To determine the on-surface material bearing capacity, engineers use a variety of tests, including field tests such as Standard Penetration Tests (SPT) and cone penetration tests (CPT), as well as laboratory tests like triaxial compression tests [2]. In some cases, shear wave velocity can also be used as an indirect method for estimating the bearing capacity of foundation soils, particularly where the depth of bedrock or other competent strata is known. This feature has made the shear wave velocity (Vs) recognized as one of the critical parameters needed to quantitatively and qualitatively assessment of the storage capacity and geomechanical resilience of the storage formation [3]. This is because shear wave velocity is directly related to the density and elastic modulus of the medium through which it travels. The shear wave velocity is a critical parameter that is used in the design of structures such as bridges, dams, and buildings, as well as in the estimation of seismic ground motion [4]. This information is used in engineering design and construction processes, as it helps determine the load-bearing capacity of rock masses [5]. Overall, shear wave velocity is critical in rock mechanics because it provides important information about the physical properties and behavior of rock masses which is essential for engineering design and construction processes. The shear wave velocity is measured by geophysical techniques such as seismic surveys and is an important property for predicting the mechanical and deformational behavior of the reservoir.

Petroleum rock mechanics serves as an essential investigative sector in the hydrocarbon exploration and production industry. Shear wave velocity derived from shear wave transmission time (Vs) exists as a pivotal dimension in petroleum rock mechanics, delineating the ultimate strength, stress-strain bearing, and deformation attributes of reservoir rocks [6]. Vs plays a crucial role in shedding light on rock mechanical properties, suiting its utilization in numerous geotechnical engineering engagements that range from geophysical prospecting to hydraulic fracturing characterization. These engagements include wellbore stability analysis, optimization of drilling methods, and limitation of probable perils like shale instability and borehole breakdown [7].

Traditionally, shear wave velocity can only be measured through costly and time-consuming field testing. The acquisition of shear wave velocity data is an integral part of petroleum rock mechanics, and it can be accomplished using two primary approaches. The first method involves extracting cores and conducting non-destructive evaluations of the sonic wave transmission in these samples using laboratory tests. This approach is expensive because of several factors, including specialized drilling equipment, highly trained personnel, and costly materials. Furthermore, the method is time-consuming and involves the transportation and analysis of core samples, which increases the total cost. On the other hand, the very limited number of coring candidate wells in a field, as well as a lack of comprehensive insight into the segmented rock column at long intervals have become significant limitations of petroleum engineers' modeling [8].

One other way to gather information about shear wave velocity is by utilizing the sonic dipole log tool or seismic data collected in the field through advanced seismography and well-logging techniques. Geophysical logging tools like dipole sonic and seismic probes can be employed to determine Vs in situ. The dipole sonic log is a highly sought-after dataset in the archives of oil and gas drilling companies' petrophysical information [4]. However, due to high demand, limited supply, and the requirement for specialized equipment, these valuable data are scarce in employers' petrophysics databases.

The use of machine learning models for predicting shear wave velocity has gained significant attention in recent years due to their potential for providing faster, more accurate, and cost-effective results. These techniques have demonstrated promising outcomes in petroleum rock mechanics prediction. Consequently, machine learning algorithms have become increasingly popular and highly sought-after for engineering estimation applications because of the following reasons:

Improved accuracy: Machine learning techniques can significantly improve the accuracy of predictions. They can analyze large datasets and identify important patterns and relationships that may not be visible to the human eye.

Time-saving: Machine learning can process large amounts of data in a fraction of the time compared to traditional methods. This saves time, reduces labor costs, and allows engineers to focus on other important tasks.

Cost-effective: Traditional methods of predicting shear wave velocity can be expensive, time-consuming, and require significant resources. Machine learning techniques are more cost-effective and require fewer resources [9].

Streamlined decision-making: By providing accurate predictions, machine learning techniques can help streamline the decision-making process for oil and gas exploration and production.

Many references support the use of machine learning techniques in reducing costs for predicting shear wave velocity for petroleum rock mechanics [10,11].

In this paper, we aim to investigate the potential use of an autoregressive deep neural network (ARDNN) for shear wave velocity prediction. Deep learning is preferred over traditional machine learning methods for big data sets because it has the ability to automatically learn and extract features from the data without the need for manual feature engineering. This makes it more efficient and effective in handling large and complex data sets. The advantage of deep learning on numerical big data sets is that it can handle high-dimensional and non-linear data, which traditional machine learning methods struggle with. Deep learning models can also scale well with increasing data size, making them suitable for big data applications. Additionally, deep learning algorithms can identify patterns and relationships in the data that may not be apparent to human analysts, leading to more accurate predictions and insights.

Autoregressive deep neural networks (ARDNNs) have recently gained popularity in time series analysis and prediction because of their ability to capture the temporal dependencies within the data [12]. The ARDNN models consist of multiple layers of artificial neurons, where each layer is connected to the previous one. Additionally, each neuron in a layer takes in not only the input at that time step but also the output of the previous time step. This allows the network to learn the relationships between the current input and the previous inputs, which is essential for accurate time series prediction [13]. In an innovative action, this research deals with deciphering how to adapt the mechanism of a deep learning time series discovery algorithm to describe the characteristics of sequenced repeating subsurface layers. ARDNNs are a type of deep neural network that combines the use of a deep neural network (DNN) with an autoregressive (AR) model. The AR model is used to capture the temporal dependencies in the data [14]. This allows the network to better predict the shear wave velocity. Since the geological sequences were deposited during a time series and have very similar structures that are repeated as successive small-scale sub-layers, it is a suitable field for applying the autoregressive system for successive geological series with time-dependent structural repetitions.

2. Research background

Machine learning algorithms have provided attractive applications in the field of engineering measures for the successful implementation of carbon capture and storage plans. Historically, researchers have relied on empirical correlations or laboratory measurements to predict Vs, but these methods are time-consuming and lack accuracy. In recent years, machine learning has emerged as a promising method for predicting Vs. Machine learning algorithms can be trained on large datasets of well-logs, seismic data, and other subsurface measurements to identify patterns and relationships that can be used to estimate Vs. Considerable scholarly work has been documented in the historical literature pertaining to this particular subject matter [4,5,8,11,15].

On the other hand, the potential application of machine learning models in different stages of the development of carbon absorption and storage projects has been promising. Some researchers have focused on the performance of machine learning in predicting carbon dioxide absorbents and solvents in the process of capturing this polluting gas. For example, Menad et al. (2019) explore the use of advanced machine learning systems in predicting the solubility of carbon dioxide (CO2) in brine. The stated objective is to apply this research in the context of carbon capture and sequestration, two critical processes in mitigating climate change. The study leverages various machine learning models, including multilayer perceptron, support vector regression, and decision tree regression, to predict the thermodynamic properties of CO2 solubility in brine under various conditions [16]. Orlov et al. (2022) proposed a novel computational approach to identify the most effective solvents for carbon dioxide (CO2) capture. The study employs the power of machine learning and considers multiple features such as thermodynamic stability, viscosity, and mass transfer kinetics to screen over 9000 potential solvents. The proposed methodology has shown promising results in identifying several effective solvent candidates for CO2 capture [17]. The research by Fathalian et al. (2021) also showcases the role of machine learning in predicting the CO2 capture performance by graphene oxide-based adsorbents. The authors demonstrate how intelligent models created and trained through machine learning algorithms can accurately predict the CO2 capturing capacity and efficiency of graphene oxide-based adsorbents under various conditions. This research marks a significant breakthrough by effectively minimizing the time and effort required to test absorbent materials while optimizing the process of CO2 capture [18]. Shalaby et al. (2021) discussed the use of machine learning tools to create a model for optimizing a post-combustion carbon dioxide (CO2) capture unit. The objective of the study is to minimize the energy consumption and associated costs of CO2 capture while maintaining high efficiency. The authors utilized data from a real industrial-scale CO2 capture system to train the machine learning model, which was then used to identify optimal parameter settings [19].

The application of powerful machine learning tools is not limited to investigating the potential of carbon dioxide absorbers. The research of Yao et al. (2023) offers insight into the potential use of machine learning (ML) in carbon capture and storage (CCS) from a geological perspective. The authors explore the role that ML can play in the selection of geological sites for CCS, identification of suitable storage reservoirs, and monitoring of the state of the reservoir over time [20].

Pressure management in candidate reservoirs for implementing CCS plans was also evaluated by machine learning. For example Pachalieva et al. (2022) developed a novel approach for pressure control in underground reservoirs by merging physics-based models and machine learning methods. Their research demonstrated promise for optimizing the management of varied subterranean reservoirs, specifically in carbon capture and storage initiatives and boosting prediction precision by incorporating physics-based models and machine learning techniques [21]. The paper by Zhong et al. (2019) proposes a new method for detecting anomalies in geological carbon sequestration sites using pressure measurements. This is a crucial issue in CCS operations, as anomalies can have serious environmental and economic impacts. The authors utilize deep learning algorithms to analyze pressure data and detect abnormal patterns [22].

The paper by Vo-Thanh et al. (2022) presents a robust machine learning approach for predicting carbon dioxide trapping indexes at geological storage sites. The authors' methodology involves the use of various machine learning algorithms and feature selection techniques to develop accurate models for predicting trapping indexes [23]. Yan et al. (2021) published a comprehensive review article on the application of machine learning in the field of carbon capture and storage. Their research explores the potential of utilizing machine learning in CCUS. The review incorporates 352 papers related to machine learning, CCUS, and their possible integration. The authors found that machine learning can enhance the efficiency and reduce costs by optimizing the CCUS process [24].

The application of machine learning in CCS has resulted in considerable development in enhancing the accuracy of CCS modeling and formulating efficient strategies. Despite this, there is a lack of research focusing on the geomechanical aspects of safe CCS site commissioning. In light of this gap, this study provides comprehensive insight into the significance of shear wave velocity (Vs) application in CCS, and how it helps in identifying suitable storage formations and characterizing reservoir properties. Additionally, the paper discusses the limitations associated with using Vs as a standalone parameter for CCS site characterization.

3. Methodology

3.1. Autoregressive deep neural network (ARDNN) algorithm architecture

An Autoregressive Deep Neural Network (ARDNN) is a type of neural network that uses a number of previous time steps in order to predict the value of the next time step [25–27]. It's often used for time series data, where a set of observations are collected over time [28,29]. The ARDNN can predict the future values of the time series based on historical data [30,31].

The architecture for an ARDNN model is described as follows [32]:

- The input layer takes in the sequence of numbers and passes it to the first hidden layer.
- The hidden layers are made up of LSTM (Long Short-Term Memory) cells. LSTM cells are recurrent neural networks that can remember the past states of the network and use that information to calculate the current state. The number of hidden layers can vary depending on the complexity of the problem, but usually, it ranges from 2 to 4 layers.
- The output layer predicts the next value in the sequence based on the current state of the LSTM cells.
- The loss function used for training the network is typically the mean squared error between the predicted values and the actual values. The optimizer used for training can be Adam, RMSprop, or SGD.

In order to make a prediction, you can feed in an input sequence of the same length as the training data and the network will output the predicted value for the next time-step. The prediction can then be fed back into the network as input along with the previous sequence to make a prediction for the next time step. This process can be repeated for as many time-steps as desired (Fig. 1). Ultimately, the autoregressive deep learning algorithm elucidates complex interdependencies between input parameters by encoding and leveraging historical information. Through iterative refinement, it refines its internal representations to proficiently model and predict future observations based on past context. This culminates in a model capable of discerning intricate relationships within the input data.

3.2. Model implementation

In this article trained the ARDNN model on the training set and optimized its hyperparameters using the validation set [33]. We used four hidden layers in the model, with each layer containing 128 neurons. The model used the rectified linear (RelU) activation function and a linear output layer. To address the potential overfitting issue, we incorporated dropout regularization into the model. We set the learning rate to 0.001 and trained the model for 500 epochs. Here is the adapted ARDNN architecture for applying on the numerical dataset:

- Input Layer
- LSTM Layer 1 (with dropout)

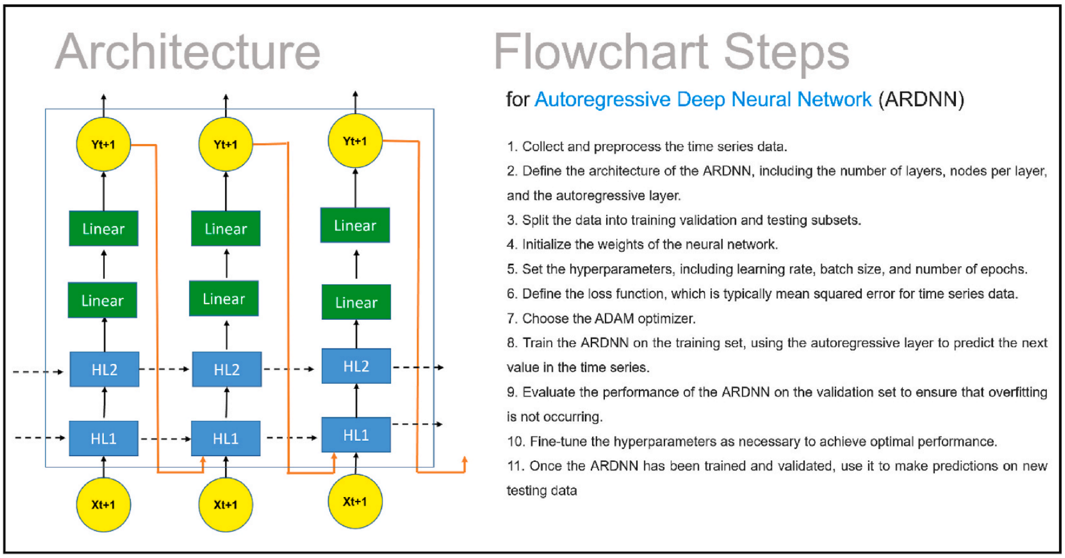

Fig. 1. Architecture and flowchart steps for the hybrid algorithm of ARDNN.

- LSTM Layer 2 (with dropout)
- Fully Connected Layer 1 (with ReLU activation)
- Fully Connected Layer 2 (with ReLU activation)
- Output Layer (with linear activation)

3.3. Decition tree (DT) algorithm

Decision trees, a well-established machine learning technique, find extensive use in evaluating a variety of datasets encompassing both classification and regression tasks [34]. These trees hierarchically organize data records into nodes and branches, governed by a set of rules, making them suitable for classifying data and handling numerical regression datasets, with a primary focus on classification [35]. Constructing decision trees for machine learning comprises three steps: a) distinguishing input (or attribute) variables from dependent (or target) variables, b) dividing data records into child nodes based on predefined rules, utilizing a splitting algorithm that evaluates attribute variables, and c) iteratively conducting further splits, creating additional layers of nodes [36]. A simplified decision tree shows the node types involved, starting from the root node, which initially divides the dataset into two subsets, forming child nodes on the second layer [37]. Subsequent divisions lead to terminal nodes with homogeneously grouped data records [38]. These trees continue to grow until the training subset achieves perfect classification, but may overfit when applied to new datasets, with increased tree complexity increasing the risk of overfitting [39].

3.4. Artificial neural network (ANN) algorithm

Artificial Neural Networks (ANNs) emulate the learning mechanisms observed in the human brain, drawing inspiration from brain structure [40]. The ANNs are prominent non-linear mathematical models highly favored in scientific and academic circles due to their inherent simplicity, adaptability, and widespread applicability [41]. The ANNs proficiently capture intricate non-linear systems by establishing intricate relationships between input and output data, circumventing the need for explicit mathematical system models [42]. These networks comprise two essential components: neurons (nodes or processing elements) and interconnections (weights). Neurons handle data processing, while interconnections facilitate communication between neurons [43].

3.5. Data collection/dataset description

The 23,000 high-quality data points, consisting of commonly available petrophysical parameters along with their corresponding dipole sonic log (DTS) data collected by well logging tools from three wellbores in one of the oil fields in southwest Iran, were gathered. The very large numerical datasets collected for the implementation of machine learning models were subjected to pre-processing for normalization, removal of noisy data and handling of missing values. Traditional petrophysical log parameters as input include caliper (CALI), natural gamma ray (GR), shallow electrical resistivity (RES-S), medium electrical resistivity (RES-M), deep electrical resistivity (RES-D), compressional wave transmission time (DTC), neutron index (NPHI), density index (RHOB), photoelectric coefficient index (PEF). Table 1 contains the characteristics and numerical data description as input and output raw parameters.

To investigate the feasibility of using ARDNNs for prediction of shear wave transition time and consequently shear wave velocity criteria, a shear wave transition time measurements dataset by sonic dipole tools was collected in different depths from several well-site in one of the Iranian giant oil reservoirs. The dataset includes measurements that had been taken at various depths with a resolution measuring a record every 10 cm. The measurement resolution of the dipole sonic log survey has been matched with the full-set logging data in the previous run of the well-logging survey by the executive operator through the Gamma-ray log coordinator index. This process is such that the gamma-ray log, which is used as an index to detect the layers, is driven into the well in one step of driving the full set log and in the next step along with the vertical seismic log. Finally, it is used for peer-to-peer matching of measurements.

The study involved collecting 23,000 data points, out of which 8000 data points were allocated for well B1, 7200 data points for well B2, and 7800 data points for well B3. The model was built using the data from wells B1 and B2 due to their highly scattered data distribution, while well B3 was employed for validation to assess the accuracy and output of the novel ARDNN algorithm. We divided the dataset (15,200 data point from wells B1 and B2) into training, validation, and testing sets. The training set contained 70% of the data, the validation set contained 10% of the data, and the testing set contained the remaining 20%. The proposed neural network model is trained using data from multiple boreholes that have been previously measured for shear wave velocity. The input to the model consists of various geophysical features of underground formations, such as which includes recorded reactions of natural

Table 1
Description of the data used in the creation of the novel ARDNN structure technique based on wells B1 and B2.

Parameters	CALI	GR	RES-S	RES-M	RES-D	DTC	NPHI	RHOB	PEF	DTS
Unit	Inch	API	Ohms-m	Ohms-m	Ohms-m	µs/ft	PU	g/cc	Barns/cm^3	µs/ft
Maximum	8.75	106.24	14.34	46224.45	15.07	98	46.67	3.17	10.00	134
Minimum	8.55	1.10	0.71	0.14	0.70	60	0.02	1.20	3.22	82
Standard deviation	0.03	18.67	2.95	1007.64	3.25	3.26	7.07	0.17	1.80	4.12
Mean	8.62	16.50	4.20	30.82	4.23	88.62	15.88	2.58	4.76	106.05
Variance	0.00	348.43	8.71	1014896.31	10.58	12.93	50.01	0.03	3.24	9.14

gamma rays, neutron log computational porosity, compaction measurement and detection of the propagation medium obtained by sonic waves transition time, electrical conductivity properties recorded by the formation resistivity log, bulk density and photoelectric properties of rocks characterized by atomic excitation. The proposed model is then tested using data from a different set of boreholes.

4. Result and discussion

Over the years, researchers have employed empirical equations to determine shear wave velocity and presented various equations for this purpose. These researchers include Carroll (1969), Castagna et al. (1985), Han et al. (1986), Krishna et al. (1989), Miller and Stewart (1991), Hossain et al. (2012), Bailey and Dutton (2012), and Lee (2013), and their respective empirical equations are listed in Table 2.

One of the critical factor's researchers consider when comparing algorithms is the R-squared value and mean squared error. Equations (1) and (2) represent these two important terms.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Vs_{Measured\,i} - Vs_{Predicted\,i}\right)^2} \tag{1}$$

$$R - Square = 1 - \frac{\sum_{i=1}^{N}\left(Vs_{Predicted\,i} - Vs_{Measured\,i}\right)^2}{\sum_{i=1}^{N}\left(Vs_{Predicted\,i} - \frac{\sum_{I=1}^{n} Vs_{Measured\,i}}{n}\right)^2} \tag{2}$$

Tables 3–5 present the results of the statistical metrics for both the experimental equations and the developed ARDNN method across test, train and validation dataset data.

The trained ARDNN model was then evaluated on the testing set, which contained data that the model had not previously seen. The results showed that the model achieved an R-squared value of 0.9906 and a mean squared error of 0.0438 (for test data), indicating that the ARDNN model is capable of accurately predicting shear wave velocity from seismic data. Additionally, we compared the results of the ARDNN model to those of a traditional autoregressive model, which showed that the ARDNN model outperformed the traditional autoregressive model.

Fig. 2 illustrates the accuracy of predicting shear wave velocity for both previous research works and the newly developed ARDNN algorithm. This figure demonstrates that there is an inverse relationship between RMSE error values and R-Square error values, meaning that as one value increases, the other decreases and vice versa. Therefore, this diagram can be used to determine the accuracy of shear wave velocity prediction performance. Tables 3–5 present the comparison of shear wave velocity prediction accuracy between the previous research works, traditional models (DT and ANN) and the newly developed ARDNN algorithm, including Krishna et al., Carroll, Lee, Miller and Stewart, Bailey and Dutton, Hossain et al., Han et al., and Castagna et al. By analyzing these results, one can determine the accuracy of shear wave velocity prediction performance.

Fig. 3a–c illustrate cross-plot reports for the dataset generated by the newly developed algorithm. These reports help determine the values for training (Fig. 3a), testing (Fig. 3b), and validation (Fig. 3c). A cross-plot chart is a graphical representation that depicts the relationship between two variables. In this chart, measured shear wave velocity is plotted on the X-axis, and the predicted shear wave velocity is plotted on the Y-axis. The data points on the chart reveal the relationship between the measured and predicted shear wave velocity. The R-Square value is a valuable tool for scientists to determine the strength of the correlation between the measured and predicted shear wave velocity. The figure's analysis confirms the algorithm's high accuracy and its ability to reduce noise in large data volumes, resulting in precise shear wave velocity prediction accuracy for such datasets.

The error histogram plot is a graphical representation that displays the distribution of errors in a dataset [51]. This type of plot is commonly used in scientific research to analyze the accuracy of measurements or predictions made by a model. In essence, an error histogram plot shows how frequently certain errors occur within a dataset and how these errors are distributed across the range of possible values. The histograms in Fig. 4 depict the shear wave velocity (Vs) prediction results of previous research studies: (a) Carroll, (b) Castagna et al., (c) Han et al., (d) Krishna et al., (e) Miller and Stewart, (f) Hossain et al., (g) Bailey and Dutton, and (h) Lee. Additionally, they include results from the deep learning algorithm (i) ARDNN, and the traditional models (j) DT and (k) ANN for the prediction of shear wave velocity. The error histogram in this figure shows a symmetrical pattern for ARDNN-based prediction and

Table 2
Determining shear wave velocity based on empirical equations and related equations.

Authors	Reference	Equations
Carroll (1969)	[44]	$Vs = 0.937562 * Vp^{0.81846}$
Castagna et al. (1985)	[15]	$Vs = 0.862 * Vp - 1.172$
Han et al. (1986)	[45]	$Vs = 0.794 * Vp - 0.849$
Krishna et al. (1989)	[46]	$Vs = 2.924 * Vp - 4170.9$
Miller and Stewart (1991)	[47]	$Vs = 0.8 * Vp - 861$
Hossain et al. (2012)	[48]	$Vs = 0.76 * Vp - 0.76$
Bailey and Dutton (2012)	[49]	$Vs = 0.75 * Vp - 562.5$
Lee (2013)	[50]	$Vs = 0.59 * Vp - 0.6$

Table 3
Shear wave velocity prediction utilizing wells B1 and B2 training data.

Research	RMSE	R-Square
Carroll	22.6728	0.4833
Castagna et al.	44.5101	0.3148
Han et al.	41.0349	0.3536
Krishna et al.	9.8023	0.5239
Miller and Stewart	33.7458	0.4342
Hossain et al.	39.2259	0.4255
Bailey and Dutton	34.3295	0.4378
Lee	29.9002	0.4517
ARDNN model	0.0497	0.9889
DT	0.1376	0.7544
ANN	0.1452	0.7497

Table 4
Shear wave velocity prediction utilizing wells B1 and B2 testing data.

Research	RMSE	R-Square
Carroll	20.6325	0.5225
Castagna et al.	39.3507	0.3403
Han et al.	36.2980	0.3821
Krishna et al.	8.0684	0.5576
Miller and Stewart	28.8469	0.4663
Hossain et al.	34.6993	0.4541
Bailey and Dutton	29.7420	0.4695
Lee	26.4209	0.4732
ARDNN model	0.0438	0.9906
DT	0.1205	0.7978
ANN	0.1575	0.7836

Table 5
Shear wave velocity prediction utilizing wells B1 and B2 validation data.

Research	RMSE	R-Square
Carroll	23.2411	0.5051
Castagna et al.	45.3582	0.3122
Han et al.	41.8365	0.3648
Krishna et al.	10.1777	0.5407
Miller and Stewart	34.4666	0.4521
Hossain et al.	40.0036	0.4329
Bailey and Dutton	35.0560	0.4534
Lee	30.5557	0.4696
ARDNN model	0.0410	0.9827
DT	0.1267	0.7907
ANN	0.1577	0.7824

traditional models, while the equations used by previous researchers, show an asymmetrical pattern. This indicates that the error distribution in the experimental methods used by previous researchers to determine the Vs value is non-normal, whereas ARDNN-based prediction produces a normally distributed error distribution. Hence, the ARDNN algorithm is more accurate compared to the previous equations' methods and traditional models, as evident from the graphs.

Fig. 5 and Table 6 present the results of applying the ARDNN algorithm to 780 data points associated with the B3 well to determine its accuracy and generalization capabilities. The results demonstrate that the ARDNN algorithm has the ability to improve performance accuracy for high volume data, and can effectively predict other parameters with high noise. Moreover, the ARDNN algorithm outperforms other machine learning algorithms such as ANN and DT are respectively stand for "artificial neural network" and "decition trees" for large datasets with high-dimensional features, and requires less pre-processing of the data while being less prone to overfitting. These advantages make the ARDNN algorithm a useful tool for predicting big data point datasets accurately and efficiently. Based on the capabilities of the ARDNN algorithm, researchers are recommended to use this algorithm for predicting important parameters in other fields with large datasets.

5. Conclusion

The purpose of this research was to predict the shear wave velocity in an oil field in southwest Iran, using 23,000 data collected from three wells (B1, B2, and B3). The researchers utilized 70% of the 15,200 data from wells B1 and B2 for training and the remaining

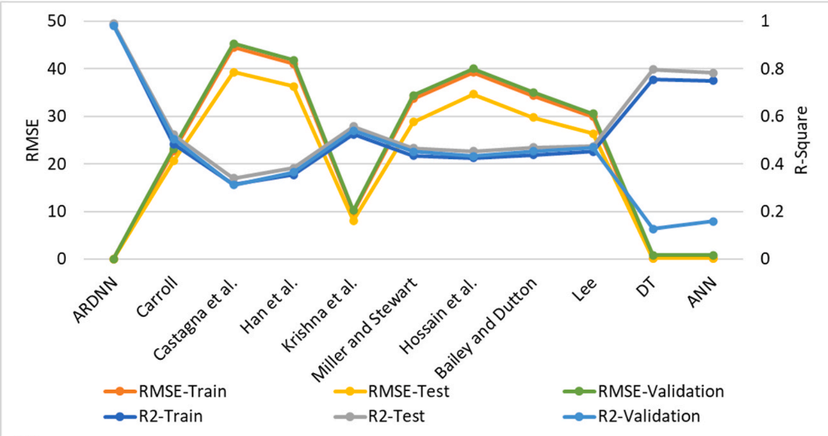

Fig. 2. R-Sure and RMSE illustration based on previous researches' work, traditional models and new developed ARDNN for prediction of shear wave velocity.

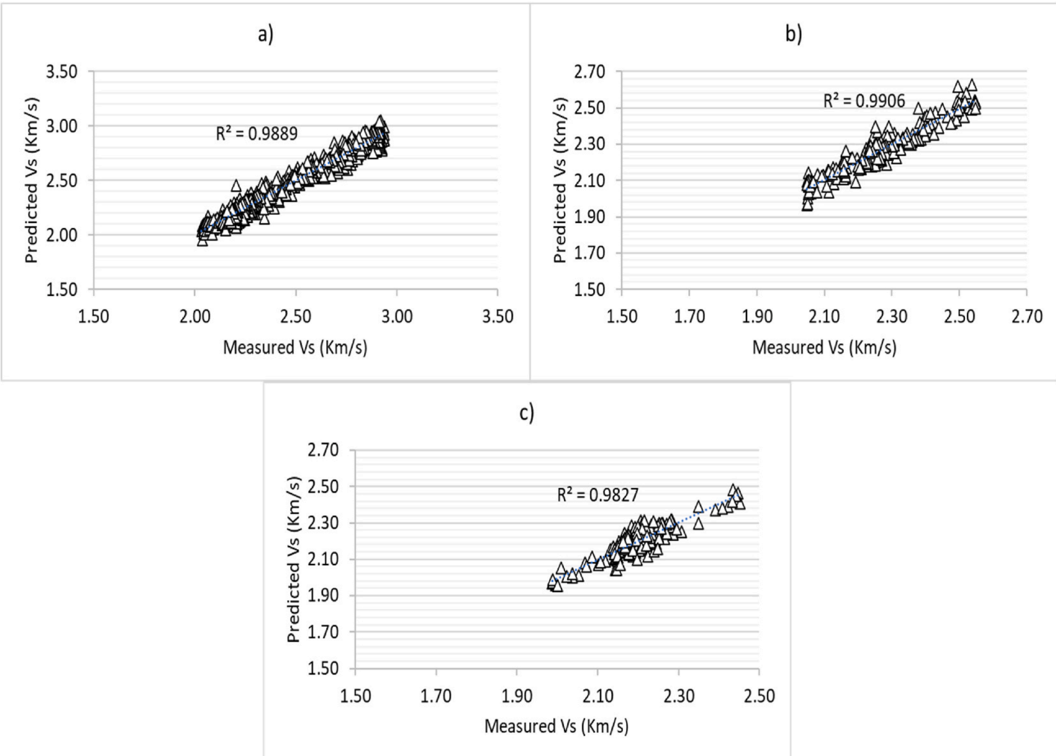

Fig. 3. ARDNN-based Vs prediction using the wells B1 and B2 dataset to determine the a) training, b) testing, and c) validation phases.

30% for testing and validation. They used the 7800 data from well B3 to develop the model. In this study, a robust and advanced ARDNN algorithm is used to predict Vs for high-volume data. The ARDNN algorithm is a powerful tool for predicting complex datasets with high-dimensional features, especially in the presence of high noise. The algorithm is able to improve the accuracy of performance for high volume data, and its ability to handle non-linear relationships between variables makes it highly effective for predicting key parameters in various fields. Compared to other machine learning algorithms, the ARDNN algorithm has several advantages such as requiring less pre-processing of the data, being less prone to overfitting, and having a higher prediction accuracy for large datasets with high-dimensional features. Therefore, the ARDNN algorithm is a valuable asset for researchers and practitioners who require accurate and efficient predictions of big data point datasets. The research results showed that the ARDNN algorithm significantly improved the accuracy of the predicted Vs values compared to the measured data. The algorithm achieved a high R-squared value of 0.9901 and a low mean squared error of 0.0438 for the test data.

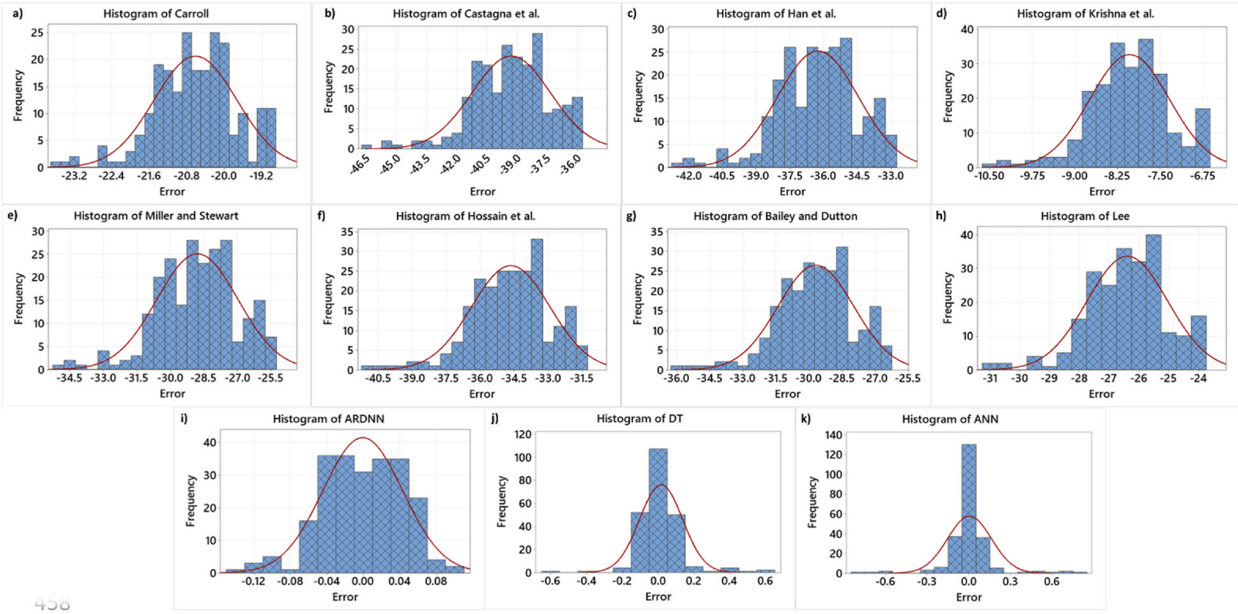

Fig. 4. Illustration of error histogram plot for previous researches (a) Carroll; b) Castagna et al.; c) Han et al.; d) Krishna et al.; e) Miller and Stewart; f) Hossain et al.; g) Bailey and Dutton; h) Lee), deep algorithm (i) ARDNN) and traditional models (j) DT; k) ANN) to prediction of shear wave velocity.

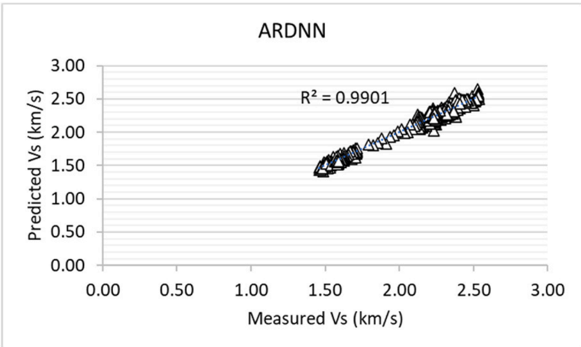

Fig. 5. ARDNN-based shear wave velocity prediction using the wells B3 dataset for generalize the model.

Table 6
Generalized new developed moder of ARDNN algorithm for shear wave velocity prediction based on B3 well data.

Research	RMSE	R-Square
ARDNN	0.0418	0.9901

One of the emerging concerns in the safety of CCS candidate sites is related to the ability of storage rock to withstand geomechanics/geotectonic stresses. Predicting the impact of these stresses on the storage rock requires accurate knowledge of the mechanical properties of the rock, including the shear wave velocity. By using an autoregressive deep neural network to predict the shear wave velocity with high accuracy, it is possible to estimate the strength of the storage rock and its potential to withstand geomechanical and geotectonic stresses over time. The potential applications of this research are vast, as it provides a new tool for evaluating the safety and effectiveness of CCS candidate sites. It can also serve as a basis for designing more robust and reliable CCS systems, which will lead to fewer accidents and environmental incidents. Moreover, this research can help accelerate the adoption and deployment of CCS systems and advance their contribution to mitigating climate change. In summary, the prediction of geomechanical bearing capacity using autoregressive deep neural network is a first major step towards safer and more reliable carbon capture and storage systems. Despite the promising results from this research, additional investigations are still required to determine its generalizability across a broad range of geological and geophysical settings. The utilization of advanced machine learning algorithms in the development of renewable energy infrastructures is a sign of progress towards achieving a sustainable future. Despite this paper having already thoroughly discussed the limitations of traditional methods in estimating shear wave transmission speed, the absence of valid shear wave velocity data (sonic dipole log) for the target fields of the study can still be considered one of its limitations. In the future, research areas for ARDNN algorithm expansion include enhanced data collection methods for more accurate shear wave velocity data, broader generalization testing, advanced model optimization for noise handling, safety assessment beyond CCS sites, environmental impact analysis, scalable adoption strategies, interdisciplinary applications, and renewable energy integration.

Data availability statement

Readers with an interest in the data may reach out to the corresponding author for access to the dataset.

CRediT authorship contribution statement

Sulieman Ibraheem Shelash Al-Hawary: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Eyhab Ali:** Validation, Software, Project administration, Data curation, Conceptualization. **Suhair Mohammad Husein Kamona:** Writing – review & editing, Software, Conceptualization. **Luma Hussain Saleh:** Validation, Resources, Project administration, Conceptualization. **Alzahraa S. Abdulwahid:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Dahlia N. Al-Saidi:** Methodology, Investigation, Data curation. **Muataz S. Alhassan:** Writing – review & editing, Investigation, Formal analysis. **Fadhil A. Rasen:** Visualization, Validation, Conceptualization. **Hussein Abdullah Abbas:** Writing – review & editing, Visualization, Resources, Formal analysis, Conceptualization. **Ahmed Alawadi:** Visualization, Validation, Software, Formal analysis. **Ali Hashim Abbas:** Writing – review & editing, Supervision, Software. **Mohammad Sina:** Writing – original draft, Validation, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors express their gratitude to the anonymous reviewers for providing valuable feedback that has enhanced the quality of our paper. Additionally, the authors extend their appreciation to Mr. Raeis for his assistance in gathering data for this article.

References

[1] J. Luo, Y. Xie, M.Z. Hou, Y. Xiong, X. Wu, C.T. Lüddeke, et al., Advances in subsea carbon dioxide utilization and storage, Energy Rev. (2023), 100016.
[2] M.A.B. Navarrete, P. Breul, R. Gourvès, Application of wave equation theory to improve dynamic cone penetration test for shallow soil characterisation, J. Rock Mech. Geotech. Eng. 14 (1) (2022) 289–302.
[3] H.G. Poulos, Use of shear wave velocity for foundation design, Geotech. Geol. Eng. 40 (4) (2022) 1921–1938.
[4] M. Rajabi, O. Hazbeh, S. Davoodi, D.A. Wood, P.S. Tehrani, H. Ghorbani, et al., Predicting shear wave velocity from conventional well logs with deep and hybrid machine learning algorithms, J. Pet. Explor. Prod. Technol. 13 (1) (2023) 19–42.
[5] M. Rajabi, H. Ghorbani, K-y Aghdam, Prediction of shear wave velocity by extreme learning machine technique from well log data, J. Pet. Geomech. 4 (3) (2022) 35–49.
[6] R. Zhang, T. Ai, L. Ren, G. Li, Failure characterization of three typical coal-bearing formation rocks using acoustic emission monitoring and X-ray computed tomography techniques, Rock Mech. Rock Eng. 52 (2019) 1945–1958.
[7] N. Mohamadian, H. Ghorbani, D.A. Wood, M. Mehrad, S. Davoodi, S. Rashidi, et al., A geomechanical approach to casing collapse prediction in oil and gas wells aided by machine learning, J. Petrol. Sci. Eng. 196 (2021), 107811.
[8] S. Rashidi, N. Mohamadian, H. Ghorbani, D.A. Wood, K. Shahbazi, M.A. Alvar, Shear modulus prediction of embedded pressurized salt layers and pinpointing zones at risk of casing collapse in oil and gas wells, J. Appl. Geophys. 183 (2020), 104205.
[9] S. Tabasi, P.S. Tehrani, M. Rajabi, D.A. Wood, S. Davoodi, H. Ghorbani, et al., Optimized machine learning models for natural fractures prediction using conventional well logs, Fuel 326 (2022), 124952.
[10] M.I. Miah, Improved prediction of shear wave velocity for clastic sedimentary rocks using hybrid model with core data, J. Rock Mech. Geotech. Eng. 13 (6) (2021) 1466–1477.
[11] M. Azadpour, M.R. Saberi, A. Javaherian, M. Shabani, Rock physics model-based prediction of shear wave velocity utilizing machine learning technique for a carbonate reservoir, southwest Iran, J. Petrol. Sci. Eng. 195 (2020), 107864.
[12] S.R. Green, C. Simpson, J. Gair, Gravitational-wave parameter estimation with autoregressive neural network flows, Phys. Rev. D 102 (10) (2020), 104057.
[13] Z. Jiang, P. Tahmasebi, Z. Mao, Deep residual U-net convolution neural networks with autoregressive strategy for fluid flow predictions in large-scale geosystems, Adv. Water Resour. 150 (2021), 103878.
[14] D. Salinas, V. Flunkert, J. Gasthaus, T. Januschowski, DeepAR: probabilistic forecasting with autoregressive recurrent networks, Int. J. Forecast. 36 (3) (2020) 1181–1191.
[15] J.P. Castagna, M.L. Batzle, R.L. Eastwood, Relationships between compressional-wave and shear-wave velocities in clastic silicate rocks, Geophysics 50 (4) (1985) 571–581.
[16] N.A. Menad, A. Hemmati-Sarapardeh, A. Varamesh, S. Shamshirband, Predicting solubility of CO2 in brine by advanced machine learning systems: application to carbon capture and sequestration, J. CO2 Util. 33 (2019) 83–95.
[17] A.A. Orlov, A. Valtz, C. Coquelet, X. Rozanska, E. Wimmer, G. Marcou, et al., Computational screening methodology identifies effective solvents for CO2 capture, Commun. Chem. 5 (1) (2022) 37.

[18] F. Fathalian, S. Aarabi, A. Ghaemi, A. Hemmati, Intelligent prediction models based on machine learning for CO2 capture performance by graphene oxide-based adsorbents, Sci. Rep. 12 (1) (2022), 21507.
[19] A. Shalaby, A. Elkamel, P.L. Douglas, Q. Zhu, Q.P. Zheng, A machine learning approach for modeling and optimization of a CO2 post-combustion capture unit, Energy 215 (2021), 119113.
[20] P. Yao, Z. Yu, Y. Zhang, T. Xu, Application of machine learning in carbon capture and storage: an in-depth insight from the perspective of geoscience, Fuel 333 (2023), 126296.
[21] B. Yan, Z. Xu, M. Gudala, Z. Tariq, S. Sun, T. Finkbeiner, Physics-Informed Machine Learning for Reservoir Management of Enhanced Geothermal Systems, 2022. Available at SSRN 4308303.
[22] Z. Zhong, A.Y. Sun, Q. Yang, Q. Ouyang, A deep learning approach to anomaly detection in geological carbon sequestration sites using pressure measurements, J. Hydrol. 573 (2019) 885–894.
[23] H. Vo-Thanh, M.N. Amar, K.-K. Lee, Robust machine learning models of carbon dioxide trapping indexes at geological storage sites, Fuel 316 (2022), 123391.
[24] Y. Yan, T.N. Borhani, S.G. Subraveti, K.N. Pai, V. Prasad, A. Rajendran, et al., Harnessing the power of machine learning for carbon capture, utilisation, and storage (CCUS)–a state-of-the-art review, Energy Environ. Sci. 14 (12) (2021) 6122–6157.
[25] A.M. Rather, Deep learning and autoregressive approach for prediction of time series data, J. Autonom. Intellig. 3 (2) (2020) 1–10.
[26] K. Gregor, I. Danihelka, A. Mnih, C. Blundell, D. Wierstra, Deep Autoregressive Networks, PMLR, 2014, pp. 1242–1250.
[27] N. Wu, B. Green, X. Ben, S. O'Banion, Deep Transformer Models for Time Series Forecasting: the Influenza Prevalence Case, 2020 arXiv preprint arXiv: 200108317.
[28] M. Stern, N. Shazeer, J. Uszkoreit, Blockwise parallel decoding for deep autoregressive models, Adv. Neural Inf. Process. Syst. 31 (2018).
[29] S. Bond-Taylor, A. Leach, Y. Long, C.G. Willcocks, Deep generative modelling: a comparative review of vaes, gans, normalizing flows, energy-based and autoregressive models, in: IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.
[30] R. Child, Very Deep Vaes Generalize Autoregressive Models and Can Outperform Them on Images, 2020 arXiv preprint arXiv:201110650.
[31] Y. Zheng, Y.-J. Zhang, H. Larochelle, A deep and autoregressive approach for topic modeling of multimodal data, IEEE Trans. Pattern Anal. Mach. Intell. 38 (6) (2015) 1056–1069.
[32] O. Sharir, Y. Levine, N. Wies, G. Carleo, A. Shashua, Deep autoregressive models for the efficient variational simulation of many-body quantum systems, Phys. Rev. Lett. 124 (2) (2020), 020503.
[33] E. Elgeldawi, A. Sayed, A.R. Galal, A.M. Zaki, Hyperparameter Tuning for Machine Learning Algorithms Used for Arabic Sentiment Analysis, 8. 4 ed, MDPI, 2021, p. 79.
[34] I. Sevilla-Noarbe, P. Etayo-Sotos, Effect of training characteristics on object classification: an application using boosted decision trees, Astronom. Computing 11 (2015) 64–72.
[35] T.B. Tesema, A. Abraham, C. Grosan, Rule mining and classification of road traffic accidents using adaptive regression trees, Int. J. Simul. 6 (10) (2005) 80–94.
[36] D. Alao, A.B. Adeyemo, Analyzing employee attrition using decision tree algorithms, Comput. Inform. Syst. Develop. Inform. Allied Res. J. 4 (1) (2013) 17–28.
[37] L. Jiao, H. Yang, Z-g Liu, Q. Pan, Interpretable fuzzy clustering using unsupervised fuzzy decision trees, Inf. Sci. 611 (2022) 540–563.
[38] M. Bevilacqua, F.E. Ciarapica, G. Giacchetta, Industrial and occupational ergonomics in the petrochemical process industry: a regression trees approach, Accid. Anal. Prev. 40 (4) (2008) 1468–1479.
[39] D. Steinberg, P. Colla, CART: classification and regression trees, The Top Ten Algorithms in Data Mining 9 (2009) 179.
[40] Y. Zeng, D. Zhao, F. Zhao, G. Shen, Y. Dong, E. Lu, et al., BrainCog: a spiking neural network based, brain-inspired cognitive intelligence engine for brain-inspired AI and brain simulation, Patterns 4 (8) (2023).
[41] Z. Jin, Autonomously Reconfigurable Artificial Neural Network on a Chip, University of Pittsburgh, 2010.
[42] B. Li, C. Delpha, D. Diallo, A. Migan-Dubois, Application of Artificial Neural Networks to photovoltaic fault detection and diagnosis: a review, Renew. Sustain. Energy Rev. 138 (2021), 110512.
[43] A.D. Dongare, R.R. Kharde, A.D. Kachare, Introduction to artificial neural network, Int. J. Eng. Innov. Technol. (IJEIT) 2 (1) (2012) 189–194.
[44] Carroll RD. The Determination of the Acoustic Parameters of Volcanic Rocks from Compressional Velocity Measurements. 6. 6 ed.: Elsevier:557-579..
[45] D-h Han, A. Nur, D. Morgan, Effects of porosity and clay content on wave velocities in sandstones, Geophysics 51 (11) (1986) 2093–2107.
[46] K.S. Krishna, D. Gopala Rao, G. Prabhakar S Murty, Y.V. Ramana, Sound velocity, density, and related properties along a transect across the Bay of Bengal, Geo Mar. Lett. 9 (1989) 95–102.
[47] S.L.M. Miller, R.R. Stewart, Effects of lithology, porosity and shaliness on P-and S-wave velocities from sonic logs, Can. J. Explor. Geophys. 26 (1–2) (1990) 94–103.
[48] Z. Hossain, T. Mukerji, I.L. Fabricius, Vp-Vs relationship and amplitude variation with offset modelling of glauconitic greensand, Geophys. Prospect. 60 (1) (2012) 117–137.
[49] Bailey T, Dutton D. An Empirical Vp/vs Shale Trend for the Kimmeridge Clay of the Central North Sea. EAGE Publications BV:cp-293..
[50] M.W. Lee, Comparison of Methods for Predicting Shear-Wave Velocities of Unconsolidated Shallow Sediments in the Gulf of Mexico, US Department of the Interior, US Geological Survey Reston, 2013.
[51] A.R.B. Abad, H. Ghorbani, N. Mohamadian, S. Davoodi, M. Mehrad, SK-y Aghdam, et al., Robust hybrid machine learning algorithms for gas flow rates prediction through wellhead chokes in gas condensate fields, Fuel 308 (2022), 121872.