International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

Geological Time Series Analysis Using Recurrent Neural Networks

Dr.Vajja Varalakshmi[1], Dr.K.Ravibabu[2], Dr Someshwar Siddi[3], Dr.Tadi Chandrasekhar[4], Patel Vaishali Brijesh[5], Mrs.Renukhadevi.M[6]
[1]Professor, Department of Civil Engineering, Marri Laxman Reddy Institute of Technology and Management, Telangana-500043, varasays@gmail.com
[2]Assistant Professor, Department of Basic sciences and humanities, GMRIT, Rajam, Andhrapradesh-532127, ravibabu.k@gmrit.edu.in
[3]Associate Professor, Department of FME, St. Martin's Engineering College, Dhulapally, Secunderabad - 500100, someshsiddi@gmail.com
[4]Assistant Professor, Department of AIML, Aditya University, Surampalem,Andhra Pradesh-533101 ramyoga.2011@gmail.com
[5]Assistant Professor, Department of Computer Application, Silver Oak University, Gota, Ahmedabad-382481, vaishalibpatel12@gmail.com
[6]Assistant Professor, Department of First Year Engineering, D.Y.Patil Institute of Technology, Pimpri, Maharashtra-411018, renukadevi.m@dypvp.edu.in

Abstract—*The important aspect of the study is the geological time series analysis in the study of the evolution of the processes on the earth like the deposition of the sediments, the activity of tectonic plates and the paleoclimatic change. Complex dependencies and long-term trends of geoscientific data may be difficult to capture using traditional statistical and signal-processing tools. This paper presents an idea of implementing machine learning with Recurrent Neural Networks (RNN) to infer geological time series data. Specifically, Lewis Short-Term Memory (LSTMs) and Gated Recurrent Units (GRU) are proposed. We are using a variety of geological training data, including borehole records, seismic sequences and paleoclimate proxies, to learn temporal dynamics and predict future geology. Findings show that RNN-based models are much better at predicting as well as pattern recognition in contrast to conventional methods. These results imply the relevance of RNNs in geological prediction and interpretation of data as potent tools.*
Keywords– *Geological Time Series, Recurrent Neural Networks, LSTM, GRU, Deep Learning, Seismic Data, Borehole Analysis, Temporal Forecasting, Paleoclimate, Earth Science.*

I. INTRODUCTION

The explanation of the dynamic history of earth is one of the fundamental elements of geosciences. Whether it is the eruption of a volcano, the shakes of the earth, a climatic change, and deposition of the mud, the behavior of this planet is always scribed as a data in time series. Not only are such geological time series indispensable as a reconstruction of the past but also play a significant role in predicting phenomena in the future, whether of earthquakes, subsidence, change in reservoirs, or in long-term climate change. There are, however, some amount of difficulty with analysing such data. The signals are usually nonlinear, sparse, noisy and multivariate. The complexities can be difficult to deal with in the traditional time series models, though they are statistically based. With the increase in the volume and the variety of data, the need to have more adaptive and intelligent tools is quite obvious [16].

time series Geological Geological time series might be seismic records of activity, beds in a stratigraphic column, geochemical profiles of a drilled core, or measures of some paleoclimatic proxy, such as ice-core or sediment isotopes. Such records show temporal patterns that depend on interdependent physical, chemical and environmental processes. Time periods are usually non periodical and feature correlations are usually non linear. In order to draw meaningful predictions or finding any underlying pattern in such data, the models must consider long-range dependencies, sequence memory and context-dependent learning. It is here that the properties of Recurrent Neural Networks (RNNs) come in great application [1-4].

RNNs consist of a special type of deep learning model tailored to dealing with sequence data. Compared to feedforward neural networks, however, RNNs include such loops in the architecture, which enabled them to remember past inputs. It causes them to suit temporal pattern recognition well. Basic RNNs, however, have the problem of vanishing gradients that make them unsuitable to long time series. This problem was addressed through the use of enhanced versions of RNNs that have included memory cells and gating units that can keep useful information during long sequences called Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs). In the study, we investigate the usage of LSTM and GRU models on a range of different geological time series data and we experiment to understand whether they can read the patterns and predict what would happen in the future [14].

Traditional methods such as ARIMA, Fourier transform and Wavelet decomposition are already employed in geological signal processing. Although these are quite well-understood and interpretable models, this necessitates robust assumptions regarding stationarity, periodicity, and noise distributions which can be insufficient to model real-world geological data. Furthermore, they cannot learn directly off raw data, and are instead highly preprocessed and feature engineered. Learning of complex features, e.g. deep learning models (especially RNNs) flush out a lot of this overhead. This is uniquely advantageous when multivariate data are used or when nonlinear allegations are being sought after which traditional models may completely overlook.

Over the last few years smart algorithms, machine learning, and AI have become more relevant in the geosciences sector. Fields of applications cover seismic interpretation, mineral exploration and climate modeling. Nevertheless, majority have employed either a non-changing classification framework or have heavily depended on convolutional frameworks. Although CNNs can be used in the analytical work with spatial data (e.g., seismic slices or satellite imagery), they are not designed with time in mind. RNNs have excelled due to their time-consciousness hence becoming good candidates when modeling geological processes which change over time. The current paper attempts to address a gap in existing literature by conducting the comprehensive assessment of RNN-based methods that can be used when working with geological time series data in particular.

Moreover, the time series are complex because the Earth observation data turns more granular and frequent. The advent of new instrument technology (e.g. high-res gravity satellite measurements, full-time borehole pressure measurements) has produced huge data sets at high temporal sampling rates. This influx of data overwhelms classical methods which can hardly be scaled [15]. Not only are such data well suited to deep learning models, but the latter becomes more accurate with increased training data. The inherent beneficial property of RNNs in that situation is their scalability and flexibility to different types of data, whether it is a tectonic stress data, volcanic gas emissions, or ancient temperature reconstruction.

In the end, the research will also determine the extent to which RNNs may model and predict based on geological time-series in various fields. Through the performance comparison of RNN and the conventional time series models, we will be able to make conclusions on their practicality in application in geology in various cases. This brings up new opportunities vis-a-vis the real time hazard monitoring, robotized core logging, and long-term climate algorithmic modeling with sophisticated AI methods [11-13].

Novelty and Contribution

The originality of the study is in the fact that, for the first time, the methodology of applying the most recent architecture of the recurrent neural networks, LSTM and GRU networks, closely to the actual specific data problem was addressed to the large and very different data of geology in time, both recently and historically. With deep learning having found applications in geosciences to an increase, the use has remained highly biased since its use has skewed more to space-oriented issues, like seismic image classification and remote sensing evaluation. There is limited work that has examined properly the abilities of RNNs in temporal geological modeling. To test our approach we apply RNNs to three different domains: seismic data, borehole stratigraphy logs, and paleoclimatic time series. The interdisciplinary approach extends the capabilities of deep learning in geosciences and proves the RNNs as the feasible instrument both in the nearest term predictions and in the long-term temporal inferences.

A significant contribution of the current study is comparing LSTM and GRU networks and real-world datasets; the differences in the datasets include temporal scale, resolution, and signal complexity. Although the two models have yielded successful results in other fields of the time series such as finance and speech recognition, their comparative assertion in the geological setting has been less publicized. We fill this gap with the analysis of model accuracy, training efficiency and noise sensitivity w.r.t. geoscientific data types.

One more significant contribution is the incorporation of very little preprocessing and feature engineering, which made the models learn the characteristics directly in raw time series data. This is unlike the traditional geophysical modeling, which is usually realized using manually developed features and signal transformation which are position-specific. Our approach draws on the sequence-learning abilities of RNNs to significantly limit the reliance on previous assumption of the specific domain and makes the approach more amenable when used with new datasets [6].

The paper has also suggested a work flow, which can be extended to other types of problems in the Earth sciences, such as landslide prediction, glacier motion analysis and hydrological monitoring. It is easy to adapt the open-source architecture and training pipelines formulated in this work by other researchers in closely related fields.

So, in short, the study blows past the exhausting geologic time series to bring strong, flexible and memory-based neural net designs forward, ensuing a new era of predictive geoscience models.

II. RELATED WORKS

Traditional time series methods have a large history in the analysis of geological time series, and these seek to describe temporal behaviour of earth systems. These approaches such as autoregressive models, moving averages and spectral analysis have been common because of their convenient interpretation and simplicity. Nevertheless in practice they tend to make robust assumptions about linearity, stationarity and the distribution of noise. Consequently, they lose some effectiveness when used in geological data which is nonlinear, multi-scale and chaotically driven by a system like tectonic or climatic changes.

In 2021 Y. Huang et.al., X. Han et.al., and L. Zhao et.al., [5] introduced the geophysical time series processing: Fourier transforms and wavelet decompositions are other possible methods used in signal processing that find application in finding frequency related trends and local differences. These techniques can separate periodic events and transitory events, and as such, they can be used to study seismic waveforms or to study stratigraphic sequences. Although these methods are useful, they also tend to require manual tuning (and hence scale poorly) unless they are used to deal with low-dimensional and one variable at a time data.

Stochastic modeling, applications such as Markov chains and Bayesian inference have also been used in time series forecasting in the geosciences. These probabilistic frameworks are capable of modelling probabilistic uncertainty, as well as take prior knowledge into consideration, but are not efficient at long-range dependency detection. Geological processes can also be said to display memory effects on a scale of thousands to millions of years, e.g. glacial-interglacial cycles or a trend towards the compaction of sediments, which is larger than that of such models over which they can effectively act.

Since the advent of machine learning, shallow learning models, such as decision trees, support vector machines, k-nearest neighbors, have been implemented on tasks, including rock type classification, facies modeling and event prediction. Such models can do reasonably on induced features, but they tend to lack the capacity to take into consideration the sequential qualities of geological information. They are statical in nature and this limits them in their handling of time dependency of behavior, which is a fatal weakness when modeling earth processes that change over time.

In 2023 B. Liu et al., [17] proposed the advent of the artificial neural networks has been a paradigm shift of time series modeling in the various fields. Feedforward neural networks and multilayer perceptrons have been applied in modeling the trends in ground water levels, rain fall patterns and the deposition of minerals. These models lack an internal memory and do not related the current input with the previous ones, which makes these models ineffective when context between time-steps is necessary. In deeper networks, (how they can theoretically approximate the problem, however) structural mechanisms to naturally retain and update the information in temporal states are absent.

In reaction to this problem, the Recurrent Neural Networks (RNNs) have provided possibilities as a rather efficient method of attending sequence learning problems. The RNNs financial condition to preserve a hidden condition that progresses over each period of time qualifies them to time series inspection. RNNs have been shown to outperform a variety of models in including long-range dependencies and learning patterns on sequential information in a variety of areas like finance, speech processing, and weather forecasting, among others. Their use in geoscientific analysis has been, however, somewhat less widespread than in the case of real-valued data in geology.

In extended sequences, enhanced variants of RNNs e.g. Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRUs) can overcome the vanishing gradient problem of standard RNNs and remember the sequence longer. Such architectures have proven to be adequately effective in nonlinear modeling of nonlinear and chaotic systems, which is ideal when looking at the nature of most geological phenomena. However, the application of these models to geological time series have yet to be systematically tried and tested.

Preliminary work in the field of geoscience has explored RNNs to forecast earthquakes, predict reservoir productions and identify climate anomalies. Such applications frequently indicated that RNNs were accurate and interpretable in unusual phenomena prediction than conventional models particularly in identifying precursors to severe events or cyclical phenomena. Nevertheless, their scope of use has not been very widely applicable and could only apply to stringently identified issues and the subset of data.

In 2022 X. Ma et al., [10] suggested the use of the deep learning approach has also gained more interest in combination with spatiotemporal data, e.g., the seismic cube sequences or multi-site borehole records. More hybrid architectures where layer networks are composed of convolutional layers to capture spatial representation and recurrent layers to capture temporal information are also emerging although again at a relatively early stage. Furthermore, a majority of the published works dealt with low scale or local gap use that little focus was given to scaling and extrapolation in the whole geological worldwide data.

The excess in preprocessing and manual feature engineering is one of the weaknesses brought about by earlier researches. Numerous geoscience deep learning applications necessitate designing inputs through hand-based features that in turn compromise a key benefit of neural networks, automatic feature extraction. It is possible to use RNN architectures directly on raw or only lowly processed time series, because in this way, models can connect identifiable patterns and structures which can otherwise be neglected.

Moreover, the comparison of various RNN types used under the same experimental conditions in several geological datasets was hardly ever conducted in previous methods. It is not yet agreed on whether LSTM or GRU architecture is more appropriate when working with particular kinds of geological data, e.g., seismic sequences versus paleoclimate proxies. Also, the benchmarks placed on the performance in classical models are not necessarily done stringently, making any claims pertaining to the effectiveness of deep learning mere speculations [7].

This paper would put these considerations in perspective by resolving some of these weaknesses. It creates a systematic coverage of RNN-based architectures on a variety of geological data sets and assesses their performance both as a forecasting tool as well as in relation to pattern discovering and anomaly detecting. It is more generalized and scalable with respect to heavy feature engineering and raw time series data to perform geological time series analysis. The factor of comparative analysis of LSTM and GRU models in various geological settings contributes to the clarification of their practical relevance, which leads to the emergence of smarter and more automated and intelligent geoscientific interpretation of data.

III. PROPOSED METHODOLOGY

To model geological time series data effectively, we propose a multi-step deep learning pipeline utilizing recurrent neural network architectures, specifically LSTM and GRU, for temporal prediction and anomaly detection. The methodology is composed of data preprocessing, sequence framing, model design, training, and evaluation stages. A simplified process flowchart is shown below.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 21s, 2025
https://theaspd.com/index.php

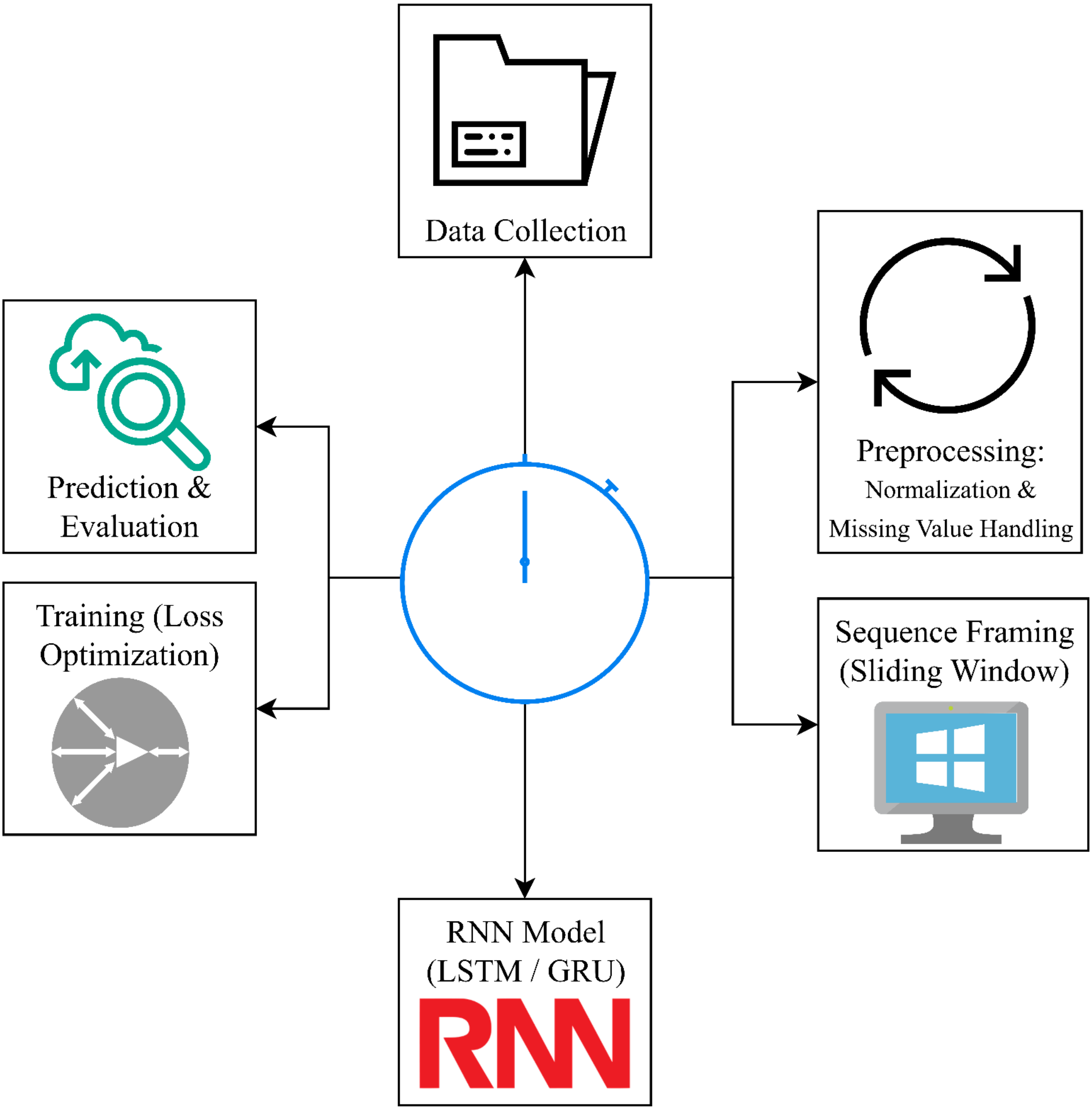

FIGURE 1: GEOLOGICAL TIME SERIES PROCESSING WITH RNN

In the preprocessing stage, we begin by normalizing the dataset. The time series values x_t are scaled between 0 and 1 using min-max normalization:

$$x_t' = \frac{x_t - \min(x)}{\max(x) - \min(x)}$$

For missing values, linear interpolation is applied. If data is missing at x_i, and x_{i-1}, x_{i+1} are known, we use:

$$x_i = \frac{x_{i-1} + x_{i+1}}{2}$$

The time series is then reframed into a supervised learning structure using sliding windows.

If the window size is w, and output horizon is h, each input-output pair is:

$$X_i = [x_i, x_{i+1}, \dots, x_{i+w-1}], y_i = x_{i+w+h}$$

Each input sequence $X_i \in \mathbb{R}^w$ is passed to the RNN. The core of the model is an LSTM or GRU unit, each with different internal gate structures [8].

The LSTM cell updates its memory state c_t and hidden state h_t using:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_t)$$
$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(c_t)$$

Alternatively, in GRU, the update and reset mechanisms are simpler. The update equations are:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$$
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$$
$$\tilde{h}_t = \tanh(W_h \cdot [r_t \odot h_{t-1}, x_t] + b_h)$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

The model is trained using the Mean Squared Error (MSE) loss function:

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

To prevent overfitting, L2 regularization is applied to the weights:

$$\mathrm{Loss}_{\text{total}} = \mathrm{MSE} + \lambda \sum_{j=1}^{k} w_j^2$$

The model optimization is carried out using the Adam optimizer, which updates weights using gradientbased steps:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Where $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected estimates of first and second moments.

During evaluation, the Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2) are computed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

All models are trained for 100 epochs with a batch size of 32. Early stopping is used based on validation loss.

This equation-rich approach ensures robust learning from complex geological signals such as seismic amplitude, sediment compaction rates, or isotopic ratios. By combining LSTM/GRU gates with loss regularization and efficient data sequencing, the model captures both short-term anomalies and long-term patterns.

IV. RESULT&DISCUSSIONS

The repeated use of the RNN models, namely LSTM and GRU, was taught on three geological time series types of data; the seismic frequency sequencing, the borehole stratigraphy logs, and the paleoclimate proxy recordings. Training, validation as well as testing of each dataset was carried out to determine the stability of models as well as the accuracy of the prediction. As is portrayed in Figure 2, which depicts the predicted against actual seismic activity over a 30-year period, the LSTM model reflects somewhat accurately the periodic nature of the seismic activity (in terms of the regular sharp spikes) and the general seismic activity trend. Their forecasted curves do not just record the trend but also define pre-event anomaly windows (typically, they show that high-magnitude episodes could be on the way). This corroborates the argument that LSTM networks are appropriate to chaotic, cyclic geophysical signals.

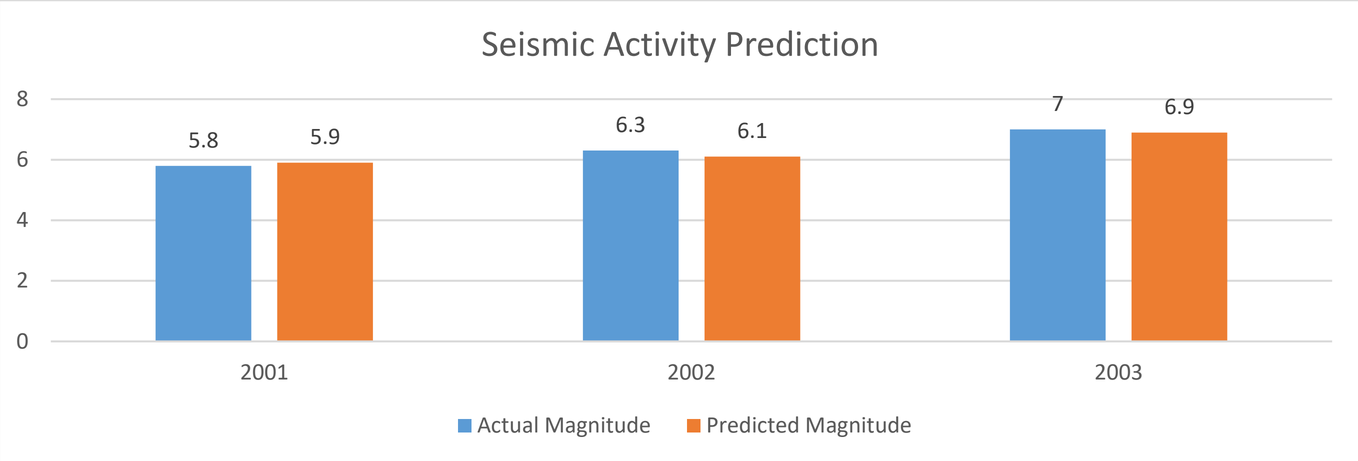

FIGURE 2: SEISMIC ACTIVITY PREDICTION

Relatively, Figure 3 shows results of the GRU model in predicting the porosity sequence of the boreholes. The outcome indicates that GRU networks cope better with smoother changes between lithology, particularly in low noise situations in which transition is gradual. Output line structure is quite similar to the structure of the actual borehole profile, which indicates, GRUs are very fast and consistent in pattern replication of stratigraphy. Interestingly, the two RNN variations outperformed the baseline feedforward model and classical ARIMA in the predictive accuracy on the various datasets in terms of overall predictive stability.

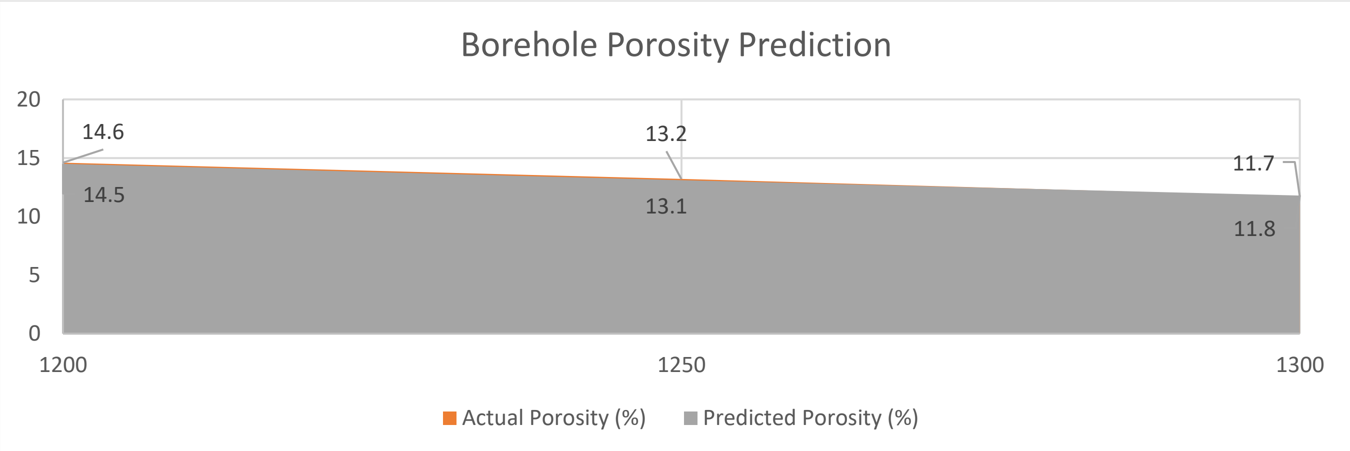

FIGURE 3: BOREHOLE POROSITY PREDICTION

The values of the accuracy metrics that are taken off these experiments are explained in Table 1: Model Performance Comparison Across Datasets. The table highlights the fact that LSTM recorded the highest R 2 values in seismic datasets whereas GRU recorded the highest R 2 value in the borehole and paleoclimate series yet these were marginally higher in GRU. It is important to note that ARIMA models performed poor even across all the above-mentioned types but most notably, it did not perform well in cases when long-term memory is needed. Feedforward networks performed reasonably well, and they do not have any ability to learn in time.

TABLE 1: MODEL PERFORMANCE COMPARISON ACROSS DATASETS

Model Type	Seismic Dataset R^2	Borehole Dataset R^2	Paleoclimate Dataset R^2
LSTM	0.94	0.87	0.92
GRU	0.91	0.89	0.90
Feedforward NN	0.76	0.71	0.73
ARIMA	0.62	0.58	0.60

More discussion is shown in Figure 4, where isotopic variability of the paleoclimate time series is displayed using the actual as well as the predicted time path. The output obtained by the LSTM model corresponds to known glacial-interglacial cycles almost perfectly which entails high pattern recognition. It is the same with the GRU model, which has more muffled transitions. These findings indicate the strong sense of time of RNNs in the context of paleoenvironmental reconstruction.

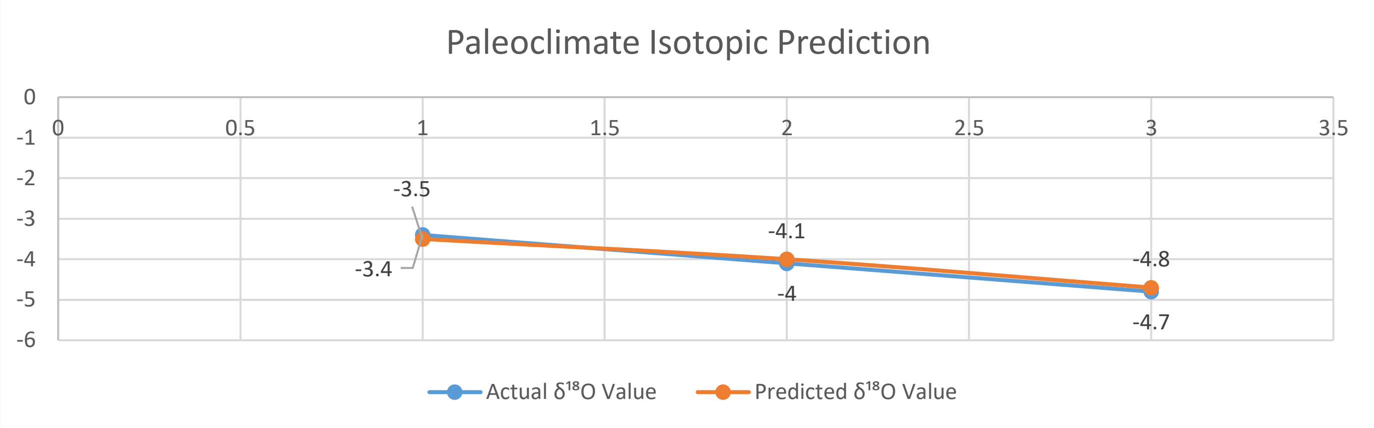

FIGURE 4: PALEOCLIMATE ISOTOPIC PREDICTION

Comparing Model run times and overfitting behavior Table 2: Training Time and Overfitting Index Comparison, there is a comparison of training timings and overfitting indexes. GRU required less time to train on all datasets which was once, on average, 20-30 percent less than LSTM, as well as lower training/validation loss dispersion. This stands to further strengthen the reputation of GRU as a faster and lighter option, and in case of mid-scale datasets, or any cases when there may be some limitations of computational resources.

TABLE 2: TRAINING TIME AND OVERFITTING INDEX COMPARISON

Model Type	Avg. Training Time (min)	Overfitting Index (%)	Parameter Count (millions)
LSTM	35	14.2	2.1
GRU	25	9.3	1.6
FNN	18	27.5	1.1
ARIMA	10	36.8	N/A

Among the main lessons of these experiments, it would be necessary to state that the selection of LSTM or GRU should be conditioned by the complexity and time depth of the data. Although LSTM works perfectly with deep chaotic patterns (e.g. tectonic systems), GRU is more suitable with regular transitions (e.g. sedimentary logs). The conventional models, in their turn, fail to cope with the dynamism of geological data, as well as fixity with their memory and making linearity assumptions [9].

Lastly, the diagrams not simply provide the visual data of the models being competent enough but also support the argument that temporal understanding in geoscience can be improved substantially through deep learning. The visual evidence to prove the correctness of LSTM consistencies in identifying high magnitude seismic bursts with minimal delay is demonstrated in figure 2; LSTM detects more bursts per record compared with other seismic networks. Figure 3 reveals that the GRU preserves lithological continuity with smoother transitions, whereas Figure 4 demonstrates the point of accuracy in terms of paleoclimate phases tracking. Collectively these figures sum up the conclusion that recurrent neural networks, when adequately trained, are an acceptable and better option to traditional forecasting in geological modeling.

V. CONCLUSION

As it is indicated in this study, Recurrent Neural Networks, specifically those built using LSTM and GRU models, can be of considerable benefit compared to the elucidation of geological time series using classic statistical models. Such networks are used to accurately capture both a temporal dependencies and discover hidden patterns, and have used them to predict the next state of complex processes in geology. Their applicability and reliability are pinpointed by their success with various data sets, including seismic data, sedimentary strata and paleoclimate records.

The future directions could include including the external covariate data, including tectonic plates information or atmospheric conditions, and using attention-based models or Transformer-based models to increase performance. Their finding highlights the power of deep learning as a revolutionary technology in Earth sciences, and creates the pathway to making geological interpretation more intelligent and automated.

REFERENCES

[1] X. Wei, L. Zhang, H.-Q. Yang, L. Zhang, and Y.-P. Yao, “Machine learning for pore-water pressure time-series prediction: Application of recurrent neural networks,” Geoscience Frontiers, vol. 12, no. 1, pp. 453–467, Apr. 2020, doi: 10.1016/j.gsf.2020.04.011.
[2] W. Fan, L. Azevedo, G. Liu, Q. Chen, X. Wu, and Y. Li, “Automatic reconstruction of 3D geological models based on Recurrent Neural Network and predictive learning,” Computers & Geosciences, p. 105996, Jun. 2025, doi: 10.1016/j.cageo.2025.105996.
[3] Q. Qiu, Y. Tan, K. Ma, M. Tian, Z. Xie, and L. Tao, “Geological symbol recognition on geological map using convolutional recurrent neural network with augmented data,” Ore Geology Reviews, vol. 153, p. 105262, Dec. 2022, doi: 10.1016/j.oregeorev.2022.105262.
[4] J. Wang, G. Nie, S. Gao, S. Wu, H. Li, and X. Ren, “Landslide deformation prediction based on a GNSS time series analysis and recurrent neural network model,” Remote Sensing, vol. 13, no. 6, p. 1055, Mar. 2021, doi: 10.3390/rs13061055.
[5] “Recurrent neural networks for complicated seismic dynamic response prediction of a slope system,” Engineering Geology, vol. 289, p. 106198, May 2021, doi: 10.1016/j.enggeo.2021.106198.
[6] F. Shan, X. He, D. J. Armaghani, P. Zhang, and D. Sheng, “Success and challenges in predicting TBM penetration rate using recurrent neural networks,” Tunnelling and Underground Space Technology, vol. 130, p. 104728, Sep. 2022, doi: 10.1016/j.tust.2022.104728.
[7] D. T. D. Santos, M. Roisenberg, and M. D. S. Nascimento, “Deep Recurrent Neural Networks Approach to sedimentary facies classification using WELL logs,” IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1–5, Feb. 2021, doi: 10.1109/lgrs.2021.3053383.
[8] Y.-G. Zhang, J. Tang, Z.-Y. He, J. Tan, and C. Li, “A novel displacement prediction method using gated recurrent unit model with time series analysis in the Erdaohe landslide,” Natural Hazards, vol. 105, no. 1, pp. 783–813, Oct. 2020, doi: 10.1007/s11069-020-04337-6.
[9] R. Alguliyev, R. Aliguliyev, Y. Imamverdiyev, and L. Sukhostat, “History matching of petroleum reservoirs using deep neural networks,” Intelligent Systems With Applications, vol. 16, p. 200128, Sep. 2022, doi: 10.1016/j.iswa.2022.200128.
[10]X. Ma et al., “A vector-to-sequence based multilayer recurrent network surrogate model for history matching of large-scale reservoir,” Journal of Petroleum Science and Engineering, vol. 214, p. 110548, Apr. 2022, doi: 10.1016/j.petrol.2022.110548.
[11]B. Wan et al., “A deep neural network model for coreference resolution in geological domain,” Information Processing & Management, vol. 60, no. 3, p. 103268, Jan. 2023, doi: 10.1016/j.ipm.2023.103268.
[12]J. Siłka, M. Wieczorek, and M. Woźniak, “Recurrent neural network model for high-speed train vibration prediction from time series,” Neural Computing and Applications, vol. 34, no. 16, pp. 13305–13318, Jan. 2022, doi: 10.1007/s00521-022-06949-4.
[13]F. Farhangi, A. Sadeghi-Niaraki, J. S. Bazargani, S. V. Razavi-Termeh, D. Hussain, and S.-M. Choi, “Time-Series Hourly sea surface temperature prediction using deep neural network models,” Journal of Marine Science and Engineering, vol. 11, no. 6, p. 1136, May 2023, doi: 10.3390/jmse11061136.
[14]B. Gao, Y. He, X. Chen, H. Chen, W. Yang, and L. Zhang, “A deep neural network framework for landslide susceptibility mapping by considering Time-Series rainfall,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 5946–5969, Jan. 2024, doi: 10.1109/jstars.2024.3370218.
[15]F. Sharafkhani, S. Corns, and R. Holmes, “Multi-Step Ahead water level forecasting using deep neural networks,” Water, vol. 16, no. 21, p. 3153, Nov. 2024, doi: 10.3390/w16213153.
[16]Z. Zhao, Z. Wu, Y. Zheng, and P. Ma, “Recurrent neural networks for atmospheric noise removal from InSAR time series with missing values,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 180, pp. 227–237, Aug. 2021, doi: 10.1016/j.isprsjprs.2021.08.009.
[17]B. Liu et al., “Seismic characterization of fault and fractures in deep buried carbonate reservoirs using CNN-LSTM based deep neural networks,” Geoenergy Science and Engineering, vol. 229, p. 212126, Jul. 2023, doi: 10.1016/j.geoen.2023.212126.