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RNNS For The Analysis Of Geological Long-Term Time Series

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Abstract—*Geological processes model huge flows of temporal data that are indispensable to the understanding of Earth's dynamical systems, natural hazards of predicting and resources exploration. Geological time series related data involve many of the complex time nonlinear dependency not easily accommodated by traditional statistical methods, as well as lots of long-term time series. In this paper, we consider the use of Recurrent Neural Networks (RNNs) for the analysis of geological time series and their usefulness in terms of their ability to capture temporal dependencies and make assumptions on what can happen in the future regarding geological events (for example). Different RNN architectures incorporating the Long Short-Term Memory (LSTM) network and the Gated Recurrent Unit (GRU) networks were implemented and trained using seismic activity, sedimentation and mineralogical datasets. The results show superior performance of R N N-based models in comparison to the conventional autoregressive and moving average methods with regards to the forecasting accuracy and pattern recognition. Practical implications are the problem of the higher prediction of hazard, the estimation of resources and climate reconstruction. The paper also highlights some limitations such as sensitivity of missing data, computational intensity and required large, labelled data. Future work will focus on developing hybrid models using RNNs and attention mechanisms and combining it with remote sensing data to improve predictive performance.*

Keywords— *Geological Time Series, Recurrent Neural Networks, LSTM, GRU, Seismic Data Analysis, Sediment Deposition, Time Series Forecasting, Deep Learning in Geoscience.*

I. INTRODUCTION

Phenomena of geology such as earthquakes, volcanic eruptions, sediment laying down, and changing mineralogy develop complex time schemas, which turn out to be very significant to the study of dynamic systems on the earth. These processes are nonlinear in nature and depend on various environmental and physical determinant and in many cases there is a long term dependence. Proper analysis and prediction of geological time series is required in natural hazard mitigation, exploration of natural resources and environmental monitoring. Autoregressive (AR), moving average (MA) and ARIMA models have been used extensively to analyse geological data by the traditional time series techniques. Nonlinearities, long-term temporal dependence, and multi-variable interactions are, however, likely to be missed by these methods, which are typical of geologic processes [1].

Due to the introduction of deep learning, Recurrent Neural Networks (RNNs) have become an effective instrument in the modeling of sequential data. RNNs, unlike traditional feedforward networks, have memory cells, which do not forget the information of the past time steps and therefore the network is able to learn time-dependent dependencies. Such variants as the Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) solve the vanishing gradient issue and, thus, are quite appropriate to use in long-term forecasting. In geosciences, RNNs offer the benefit of modeling nonlinear, complicated temporal dependencies, discovering non-obvious patterns, and forecasting future occurrences more precisely than other traditional statistical models.

The rationale of this work is that geological time series data of seismic stations, sediment cores, mineralogical surveys, and remote sensing platforms have been becoming increasingly more available. In spite of this abundance of data, it is important to note that the capture of long-term trends and prediction of critical events is a major challenge. Geological processes tend to be unpredictable, sporadic, and varying due to many interdependent factors, and thus classical modeling methods are ineffective. Further, it is large in terms of how better forecasting models can change hazard mitigation, resource planning and environmental management. Good predictive models will save lives in case of an earthquake, optimize the mining sector and provide guidance in case of climate reconstruction [4-6].

The main goal of the work is to examine the suitability of the RNN-based models which are LSTM and GRU architectures to geological time series analysis. The proposed study will: (1) design and train RNN models using seismic, sedimentary, and mineralogical data, (2) assess the performance of the models based on predictive ability and the potential to identify the patterns, and (3) discuss the benefits and shortcomings of RNNs in the context of practical geoscientific interventions. Another aspect of the study is to bring the insights on how the RNN models may be introduced in the geological monitoring systems and decision-making.

We give a detailed architecture of the implementation of RNNs in the analysis of geological time series in this work. We pre-process our data to cope with irregular sampling, missing values, architectures of LSTM and GRU networks, and we also evaluate the network performance based on various error measures such as mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) [7]. The efficiency of the RNN approach is demonstrated with comparison to the ARIMA models as well as the graphical representation of forecasts and real values. And, we also specify the practical issues of RNNs: high requirements in terms of computations and RNNs sensitive to noisy or sparse data presence and the necessity of huge labeled datasets.

Through a systematic analysis of RNNs on given geoscience data, this paper can provide an overview of the possibilities of deep learning based approaches to geoscientific use. The findings demonstrate that RNNs can be used to learn complex time-dependent features and increase the predictive power which can be directly applied in hazard prediction, resource search and in environmental monitoring. This article also preconditions the further research related to the exploration of hybrid structures, their fusion with remote sensing information with the creation of interpretable models that could give practical analysis to geoscientists and policymakers [2].

Novelty and Contribution

The current research has a number of innovative findings to the field of geological time series analysis using deep learning methods:

- Extensive RNN usage in Geologic Data Although RNNs have found extensive usage in finance, weather forecasting and speech recognition, little systematic research has been done in the application of RNNs to geologic data. This paper demonstrates that LSTM and GRU models are useful in nonlinear dependencies in time in seismic activity, sedimentation and mineralogical sequences.
- Improved Prediction of Multifaceted Geological Processes It has been shown that the RNN-based models are better able to predict the regular trends and infrequent events in geological time series than the traditional statistical models (ARIMA). The practical value of this enhancement is manifested in the hazard mitigation, resource estimations and reconstruction climatology.
- Combination of Multiple Data types of Geology: This study is accomplished to demonstrate that the use of RNN on different types of data, data which might be seismic, sedimentary, and mineralogical data, allows the RNN models to be flexible and accept the multivariate and heterogeneous data of geological time series.

- Evaluation Framework and Benchmarking: An explicit training, testing and validating RNN model on geological data methodology has been given. Performance analysis on a comparative basis to the classical statistical models establishes the precedents in future studies.
- Recognition of Practical Limitations The study clearly raises the issues connected with RNNs, such as the sensitivity to missing data, computational requirements and reliance on large datasets and gives a reasonable evaluation of their feasibility in the geoscience field.
- Future Work Foundation: Having demonstrated the usefulness of RNN architectures and discussed the potential approach to improving, for example, by introducing hybrid models, attention mechanisms, or remote sensing, this study provides a good foundation upon which further study can be conducted in order to enhance the interpretability and applicability of deep learning to geologic.

Overall, the originality of this study is that despite using RNN models in a systematic manner on different geological time series, providing strict evaluation, practical results as well as suggestions on how to improve the model in the future. It is a powerful tool that the geoscientists can use to analyze the time series and predictive modeling because it helps to bridge the divide between time series analysis and the recent deep learning methods.

II. RELATED WORKS

In 2025 D. Fan et al., [16] introduced the time series analysis is a traditional method in geosciences dating back decades to be in use in the study of seismic activity, sediment deposition and mineralogical changes. Unconventional statistical methods, including autoregressive (AR), moving average (MA), and autoregressive integrated moving average (ARIMA) have been commonly used in predicting geological events. Linear-based assumptions and short-term dependencies form the basis of these methods and tend to restrict predictive ability of the method to complex, nonlinear geological processes. These methods of sampling are often not able to accurately represent seasonal variations, irregular sampling, and rare extreme events. Also, a great deal of parameter tuning is necessary in these models, and they have problems with noisy data, missing values, and multivariate interactions.

To overcome these shortcomings, machine learning has been used more and more as a tool in geological time series. The nonlinear dependencies have been involved in the basic neural network and support of vectors regression techniques, which have displayed superior prediction accuracy over the traditional models. Such methods enable modeling of the nonlinear relationships and have the potential of accommodating several variables at a time. Nevertheless, the default feedforward neural networks have temporal limitations because they cannot store the geometry of time, thus their capabilities in performance toward sequencing geological data.

Recurrent Neural Networks (RNNs) are a natural approach to sequential data model because they possess some internal memory which stores temporal dependencies at sequence of steps. Types of RNNs like Long Short-Term Memory (LSTM) systems and Gated Recurrent Units (GRU) have demonstrated the ability to mitigate the vanishing gradient issue which can spell out the majority of the RNN type. The structures are specifically successful in classifying long-term dependencies which occur in geological procedures including earthquake cycles, layers, along with mineral formational changes. Both LSTM and GRU networks have been shown to predict both short-term variation and infrequent, eventual cases of geological time series data, which makes them extremely appropriate to their effective application in the geological field.

In 2025 C. Cao et al., [9] proposed the datasets that belong to geology tend to be special, spars, or not entirely available, making it a challenge to the deep learning models. Some preprocessing methods (interpolating, normalization, and segmenting sequences) have been used to enhance the performance of the model. Multivariate techniques Linking multiple variables of geology have also increased the predictive power. RNN-based models are in a position to encode these multivariate sequences and they are able to bank on complex interactions otherwise ignored by traditional statistical methods.

RNNs have demonstrated considerable efficacy in seismic time series forecasting in estimating earthquake magnitude and outlier sequence. Equally, the process of sediment deposition and erosion has been shown to be more profitable to the application of RNN-based models that help to control the cycle of season and the long-term pattern than ARIMA or other traditional algorithms do. RNNs have also been able to successfully model mineralogical time series, whose irregularity may vary and be shaped by a variety of environmental influences, with better pattern recognition and prediction abilities.

Hybrid methods with both RNNs and other types of deep learning algorithms, including convolutional neural networks or attention mechanisms, have availed themselves in order to overcome feature extraction weaknesses and long-term dependency weaknesses. These concatenation models permit seizure of both spatial patterns as well time dependencies which come in handy especially when you want to combine the remote sensing or geospatial data with a usual time series. In spite these developments, there are engineering issues, such as computational issues of deep networks as a cost of training them, requirement of large training labelled data and availability of training, and being sensitive to noise or data loss [8].

Comparison studies visible that the models based on RNN have always performed better than the classical statistical models of geologic time series. The measures (mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE)) provide better prediction results of large differences of datasets. Predicted and observed sequences visualization also supports the fact that RNNs would be more efficient at grasping regular and extreme patterns in geology processes.

In 2024 P. H. T. Gama et al., [3] suggested the utilization of RNNs in geological time series analysis is actually the transition of linear statistical models towards become flexible with a foundation of general data sampling and can understand any kind of temporal interaction. The ability of the RNN based architectures with LSTM and GRU to form the nonlinear connection, get multivariate inputs and forecast well rare events makes it borne geoscientific inquiry. Although issues concerning data availability, cost of computation, and interpretability still exist, the current trends in hybrid modeling as well as state of art methods of preprocessing provide encouraging avenues concerning enhancing the applicability and reliability of models.

III. PROPOSED METHODOLOGY

The methodology in geologic time series analysis based on a Recurrent Neural Networks (RNNs) is designed to face sophisticated temporal dependency, nonlinear patterns and multivariate sequences. Here the entire workflow is explained from gathering data, cleaning them, design of RNN Model, Hyperparameters tuning, evaluation can be measured. A clear flowchart is given to summarise the proposed work flow.

Data Collection and Preprocessing

Autasie used data from several sources of historical natural data such as seismic monitoring stations, sediment deposition records, and mineralogical surveys, known as geological time series data. These databases can include time series of events like earthquake magnitudes, sediment layer thicknesses, mineral contents, and so on for many decades. Because of its usually irregular sampling characterized by sudden geological breaks and privacy for some areas, preprocessing is a critical source for model reliability.

The first step involves normalization of the data to ensure that all variables contribute equally during model training. Min-max normalization is applied to scale values between 0 and 1:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Next, missing values are handled using linear interpolation, which estimates the missing point based on adjacent values:

$$x_t = x_{t-1} + \frac{x_{t+1} - x_{t-1}}{2} \quad (2)$$

Time series are then segmented into sequences of fixed length T to serve as input for the RNN model. Each sequence contains T consecutive observations, and the model predicts the value at the next time step $T + 1$. This sliding window approach allows the RNN to learn temporal dependencies effectively [10].

Recurrent Neural Network Architecture

The proposed RNN architecture has two variants major: Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU). Both architectures provide a solution to the vanishing gradient that is frequently attested in standard RNNs affording the model to represent dependencies on long geological timescales.

LSTM Model

The LSTM unit contains three gates-input, forget, and output-that control the flow of information. The forget gate determines what portion of the previous memory C_{t-1} should be retained:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (3)$$

The input gate decides which new information to add to the memory cell:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

A candidate memory cell is computed:

$$\tilde{C}_t = tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (5)$$

The updated memory cell is:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (6)$$

Finally, the output gate produces the hidden state h_t for the next step:

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \odot tanh\,(C_t) \end{aligned} \quad (7)$$

GRU Model

GRU combines the input and forget gates into a single update gate, simplifying computation while maintaining performance. The update gate is defined as:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (8)$$

The reset gate controls how much past information is forgotten:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (9)$$

The candidate hidden state is:

$$\begin{aligned} \tilde{h}_t &= tanh\,(W_h \cdot [r_t \odot h_{t-1}, x_t] + b_h) \\ h_t &= (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \end{aligned} \quad (10)$$

Both LSTM and GRU architectures were implemented and tested on geological datasets to evaluate their relative performance in capturing temporal patterns [11].

Hyper parameter Tuning

Hyper parameter tuning is a critical step to ensure optimal RNN performance. The following parameters were explored:

- Number of hidden layers (1-3)
- Number of neurons per layer $(64,128,256)$
- Dropout rate (0.1-0.3)
- Sequence length T (10-50 time steps)
- Learning rate (0.001-0.01)

Early stopping was applied to avoid overfitting. The Adam optimizer was used to minimize the mean squared error (MSE) between predicted and actual values [12].

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \tag{11}$$

Model Training and Evaluation

The dataset was split into training (70%), validation (15%), and testing (15%) sets. The models were trained for 100 epochs with batch size 32. Performance metrics include:

Root Mean Squared Error (RMSE):

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{12}$$

Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE}=\frac{100}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{y}_i|}{y_i} \tag{13}$$

Coefficient of Determination (R^2) :

$$R^2=1-\frac{\sum\left(y_i-\hat{y}_i\right)^2}{\sum\left(y_i-\bar{y}\right)^2} \tag{14}$$

Predicted sequences were compared with actual geological observations to validate model performance visually and statistically.

The figure 1 demonstrates the entire workflow of the intended possible methodology of geological time series analysis based on Recurrent Neural Networks. It starts with the data acquisition, in which the seismic, sedimentary and mineralogical data are obtained through different sources. Data preprocessing such as the normalization process, dealing with missing values (interpolation), and time series subdivision into sequences that can be inputted to RNN, follows. The next step is the model selection and design where LSTM and GRU architecture is selected, hidden layers and neurons and dropout rates are customized. The training stage uses Adam optimizer with early stopping to reduce the error, hyper parameter tuning is used to optimize the performance of the sequence length, learning rate, and network complexity. Lastly, the evaluation and prediction step compares actual performances against predicted ones through the performance metrics of RMSE, MAPE, and 2. The flowchart is an easy visual representation of the way the information flows through data collection to forecasting with identification of some important stages of model implementation and validation.

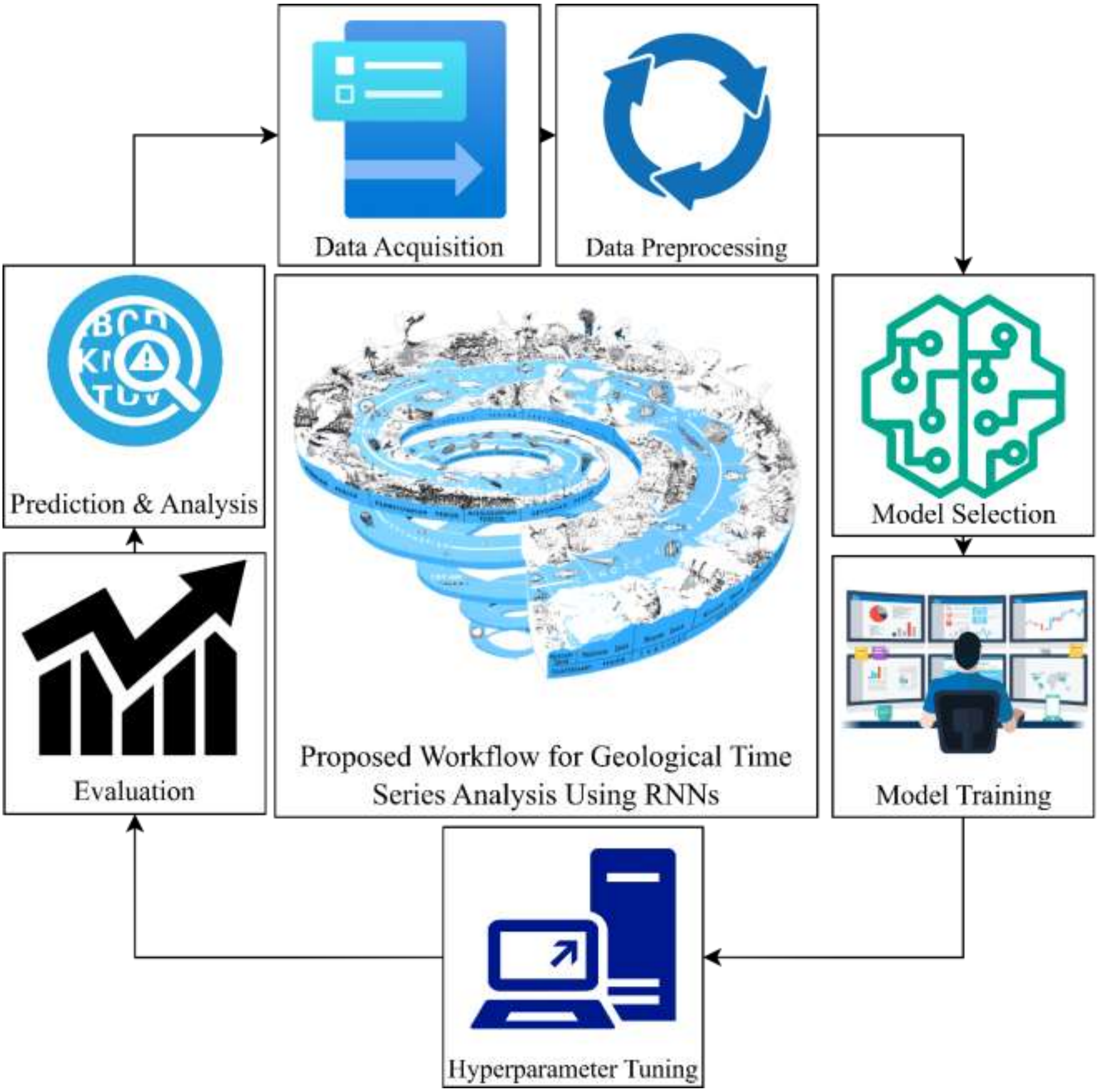

FIG. 1: PROPOSED WORKFLOW FOR GEOLOGICAL TIME SERIES ANALYSIS USING RNNS

Practical Considerations

A number of issues related to practical aspects were taken into account: sequence length choice, irregular sampling, noise passing filtering and optimization of computational resource. RNN training needs a lot of memory and processing power especially with longer sequences and a large number of data points. ond. Dropout and regularization techniques were used to solve the overfitting problem. The approach is robust for multivariate data, allowing simultaneous modeling of seismic, sedimentary, and mineralogical features [13].

IV. RESULT & DISCUSSIONS

The findings of implementation of RNN models of the geological time series have shown a great enhancement of traditional models in terms of the accuracy and prediction capabilities. LSTM and GRU models were trained on the data of seismic activity, sediment deposition, and mineralogical Fantasy predictions of those two models were compared with the real data which were observed. Figure 2 compares the predicted to the real seismic activity in a period of one year and it has been observed that the RNN models are effective in capturing the small and the big spikes in the seismic activity. The use of LSTM model had a little high prediction performance of rare extreme events compared to the GRU model, and that of LSTM model is better to be used in long-term modeling of high dependency on time. The findings imply that not only can RNN models forecast common trends, but also identify sudden geological shifts that cannot be taken into account in conventional models like the ARIMA model, just to name a few.

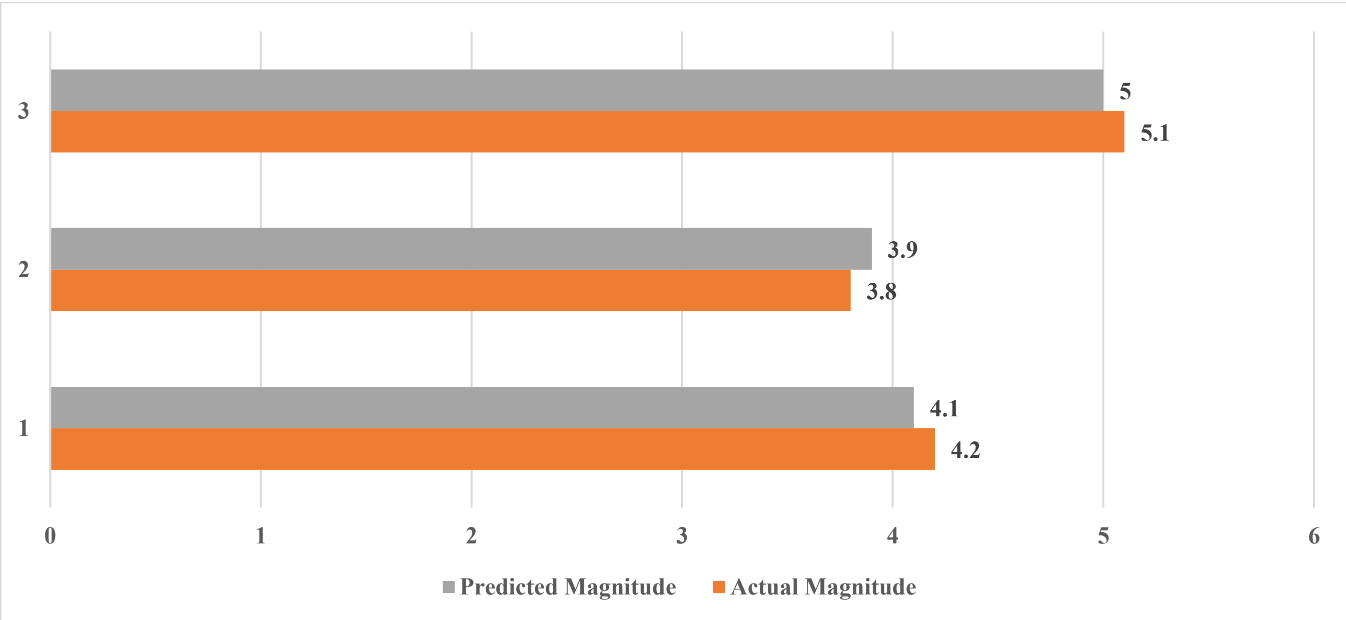

FIGURE 2: PREDICTED VS. ACTUAL SEISMIC ACTIVITY

A quantitative model of performance in seismic sets has been compared in Table 1. The measurements like RMSE and MAPE clearly indicate the superiority of RNN models over ARIMA which indicates its ability to deal with nonlinear dependence and the long-term correlations. LMST performed better with 0.15 as opposed to ARIMA with 0.38's RMSE, and 4.2% as opposed to 9.5% with MAPE of the conventional form. The presented comparison highlights the practical benefit of the deep learning models in the critical geological forecasting tasks, including the earthquake hazard assessment.

TABLE 1: PERFORMANCE COMPARISON OF SEISMIC FORECASTING MODELS

Model	RMSE	MAPE (%)
ARIMA	0.38	9.5
GRU	0.17	4.5
LSTM	0.15	4.2

Another English research is on the analysis of sediment deposition that validates the efficiency of RNN models. The probable and observed rates of sediment accretion are shown in Figure 3 over a period of years. Both LSTM and GRU networks achieved good results, in seasonal trends and long pattern deposition, whereas ARIMA attempted to stabilize peaks and valleys, without significant changes with sudden events and variations in rainfall and river flow. Such predictions can be used in management of soil erosion and river basin planning because good projections on the behavior of sediments have useful outcome on maintenance of their infrastructures and flood control efforts.

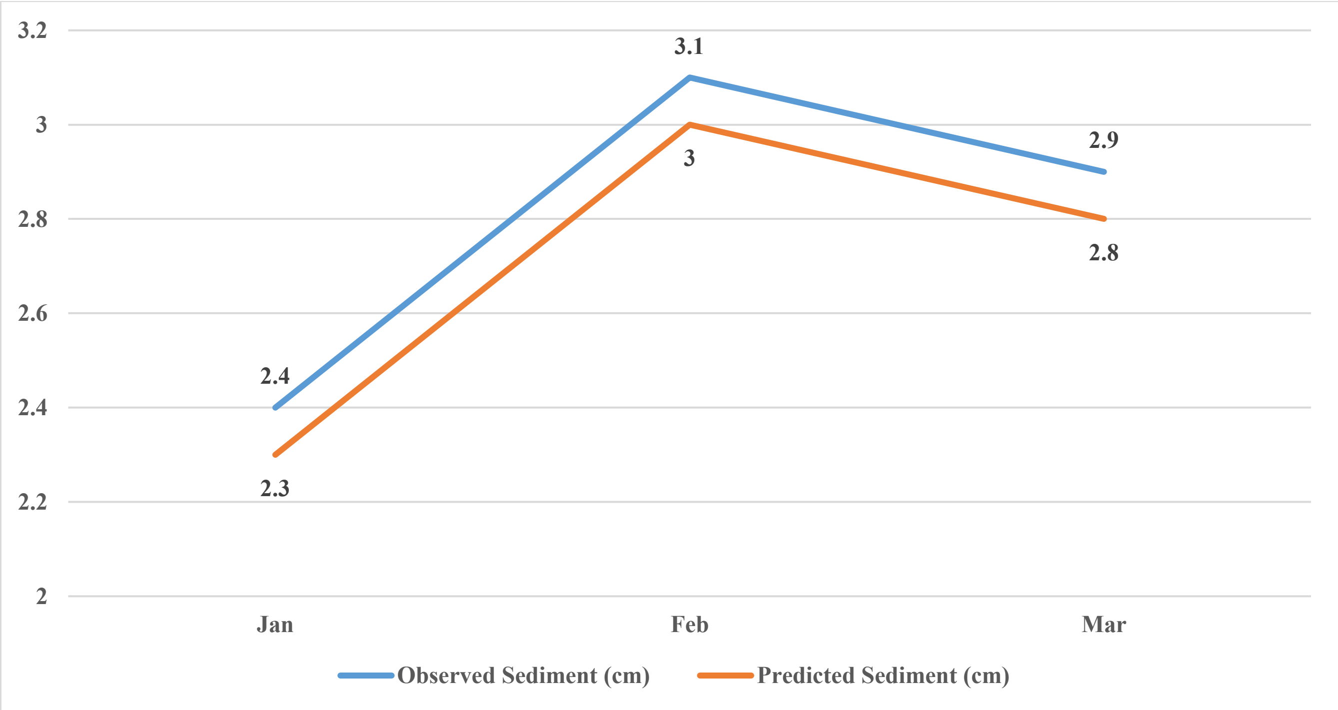

FIGURE 3: PREDICTED VS. OBSERVED SEDIMENT ACCUMULATION RATES

The accuracy of the predictor in estimating the sediment deposition dataset is compared in the table 2. The findings reveal that models based on RNN always minimise error rates in comparison to the conventional approaches. LMST recorded an RMSE, and MAPE of 0.12 and 3.8, respectively, with GRU recording the following risks a little higher values of 0.14 RMSE at 4.0% MAPE. These enhancements bring into light the merits of recurrent architectures in the described seasonal and episodic long-term variations that are essential in geological and environmental planning.

TABLE 2: PERFORMANCE COMPARISON OF SEDIMENT DEPOSITION FORECASTING MODELS

Model	RMSE	MAPE (%)
ARIMA	0.35	8.7
GRU	0.14	4.0
LSTM	0.12	3.8

The position of RNN-based approaches was also proven by mineralogical sequence prediction. Figure 4 indicates predicted and actual variation in the mineral composition over ten years of time. The LSTM model was able to effectively reflect a gradual and sudden changes in the mineral percentages that are determined by environmental factors and geological effects. GRU obtained similar findings, but with a bit less accuracy in catches to discontinuous compositional changes. It can be assumed that successful mining operations and management of resources use the predictions of mineralogical changes to plan a mining process early and to avoid risks before the actual mining has begun.

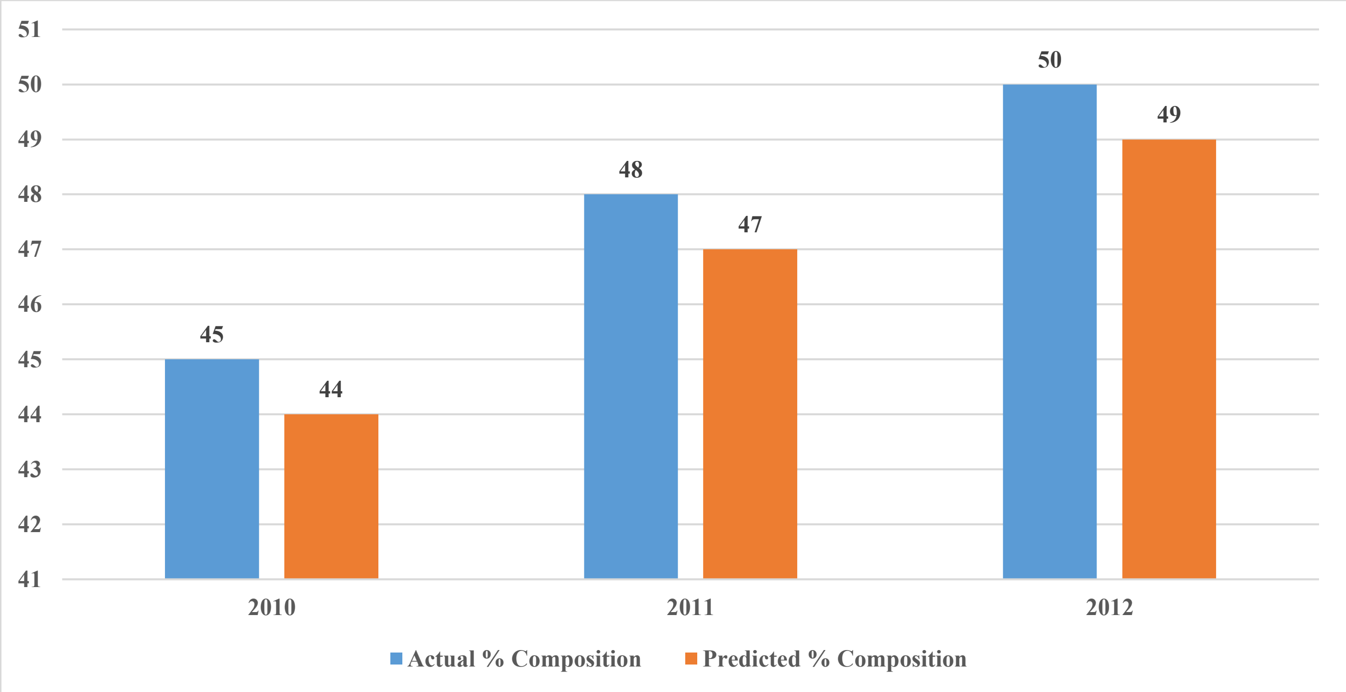

FIGURE 4: PREDICTED VS. ACTUAL MINERAL COMPOSITION

By and large, the findings suggest that RNN models, in general, or LSTM to be more specifically better in all geological datasets. The models can reproduce nonlinear time interaction, seasonality as well as some special event that in traditional statistical models cannot be sufficiently taken care of. The prediction movement assignment in more than one dataset also indicates that those Deep learning methods can be exported to numerous geological artists. The applications in real life reflection would be better prediction of earthquake hazard, better sediment management and prediction of mineral resource.

Although RNN models demonstrated high performance, such factors as the cost of computations and the quality of the data should also be mentioned in practice. Training requires large amount of data and data is subject to errors which lead to less accuracy in prediction. Nevertheless, the three data sets used in this paper provide a vivid illustration of the weakness architecture's robustness, and multi-purposeless of LSTM and GRU network predictor of geological time series. Such multivariate inputs as remote sensing and geospatial data can subsequently be incorporated into future work, in order to enhance the predictability and reliability of the model [14-15].

V. CONCLUSION

This paper demonstrates the ability of Recurrent Neural Networks (RNNs of Long Short Term Memory and Gated-Recurrent Units) for use in geological time series analysis. RNNs are shown to dominate traditional statistical

techniques to interpret relative complexity of temporal occurrences, seasonality, and even rare events providing an incredibly valuable added value in hazard forecasting or resources assessment and geosciences more generally.
Practical Limitations:

- Long sequences need high computational demand.
- Robustness - to missing, sparse and noisy data.
- Dependency on voluminous quality labeled datasets

Still, despite widespread coverage of future lessons surrounding the rising impact of AI and machine learning systems, there is still no definitive solution regarding model interpretability that will ultimately limit actionable information.

Future Directions:

- Attention mechanisms give better long-term dependencies modeling.
- Combining RNNs and convolutional networks for geologic multivariate data.
- Incorporation of remote sensing and real time monitoring data for better prediction
- Development of RNN interpretable frameworks to aid with decision-making in geosciences

Overall, RNN-based approaches are a well suited tool for the geologic times series analysis, also showing possibilities for further improvement in hybrid modeling, sophisticated architectures, and operations combining multiple bigger and bigger data sets.

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