ARNN: Attentive Recurrent Neural Network for Multi-channel EEG Signals to Identify **Epileptic Seizures**

Salim Rukhsar^{a,*}, Anil K.Tiwari^a

^aDepartment of Electrical Engineering, IIT Jodhpur, 342037, India

Abstract

We proposed an Attentive Recurrent Neural Network (ARNN), which recurrently applies attention layers along a sequence and has linear complexity with respect to the sequence length. The proposed model operates on multi-channel EEG signals rather than single channel signals and leverages parallel computation. In this architecture, the attention layer is a computational unit that efficiently applies self-attention and cross-attention mechanisms to compute a recurrent function over a wide number of state vectors and input signals. Our architecture is inspired in part by the attention layer and long short-term memory (LSTM) cells, and it uses long-short style gates, but it scales this typical cell up by several orders to parallelize for multi-channel EEG signals. It inherits the advantages of attention layers and LSTM gate while avoiding their respective drawbacks. We have evaluated the model's effectiveness through extensive experiments with heterogeneous datasets, including the CHB-MIT and UPenn and Mayo's Clinic datasets. The empirical findings suggest that the ARNN model outperforms baseline methods such as LSTM, Vision Transformer (ViT), Compact Convolution Transformer (CCT), and R-Transformer (RT), showcasing superior performance and faster processing capabilities across a EEG datasets. The code has been made publicly accessible at https://github.com/Salim-Lysiun/ARNN.

We proposed an Attentive Recurrent Neural Network (ANN), which rechas linear complexity with respect to the sequence length. The proposed than single channel signals and leverages parallel computation. In this at that efficiently applies self-attention and cross-attention mechanisms to convectors and input signals. Our architecture is inspired in part by the attention and it uses long-short style gates, but it scales this typical cell up by several inherits the advantages of attention layers and LSTM gate while avoiding the effectiveness through extensive experiments with heterogeneous datasets, it datasets. The empirical findings suggest that the ARNN model outperform (ViT), Compact Convolution Transformer (CCT), and R-Transformer (RT), capabilities across a EEG datasets. The code has been made publicly access the such as in natural language processing particles. Second, while passing from one-temporal data, such as in natural language processing [2], and image recognition [3]. They have been so successful for a number of reasons. To begin with, training Transformers is more efficient on today's accelerator technology since all sequence elements are processed in parallel. Sequences in an RNN are processed one at a time, which requires a large batch size and thus longer training time. Second, while passing from one sequence to the next, an RNN has to condense the preceding sequences into a single hidden state vector. However, the amount of previous sequences that the RNN can encode is constrained by the size of the state vector. Transformer, on the other hand, is not restricted in its ability to process past sequences. Third, attention in a loc mation is efficient even across longer distances. The information may be lost by the forget gate in an LSTM when moving forward, leading to vanishing gradients during backpropagation. In pracbe lost by the forget gate in an LSTM when moving forward, leading to vanishing gradients during backpropagation. In practice, this implies that LSTM faces problems in sending enriched information over a large number of sequences, which is significantly less than the handling ability of the attention mechanism of Transformer [4].

Despite the stated benefits, Transformers do have drawbacks. Processing lengthy documents, such as technical articles or

Email address: rukhsar.1@iitj.ac.in (Salim Rukhsar) URL: https://github.com/Salim-Lysiun (Salim Rukhsar) ultra-high pixel images, is hampered by the quadratic computational complexity of self-attention with respect to the sequence length [2, 5, 6]. Original Transformer architecture inherently does not understand or handle the relationships and interactions between different channels or variables in multichannel time series data. Furthermore, the self-attention does not find effective local dependencies and hence loses information in time series data that consists of fine-grained local information [6].

This paper presents a framework that brings both capabilities of attention and recurrence, as shown in Fig. 1. The aforementioned restrictions are all addressed in our implementation of the Attentive recurrent neural networks (ARNN), which is unique in several key respects. In this novel architecture, we combined self and cross-attention for capturing local features in a local window and a recurrence gate to condense this information to form a global feature. Instead of sequentially processing individual sequences, our recurrent cell functions on the local window of a segment, as illustrated in Fig. 2. Within each local window, all sequences are simultaneously processed. Similarly, the recurrent cell operates on a block of state vectors rather than a singular vector. Consequently, the recurrent state size surpasses that of an LSTM by orders of magnitude, significantly enhancing the model's ability to retain past information. local window-based sequence processing aids in propagating information and gradients over longer distances, given the considerably fewer recurrent steps, thereby reducing the number of forget gate applications and training time.

This ARNN cell architecture is capable of handling multi-

^{*}Corresponding Author

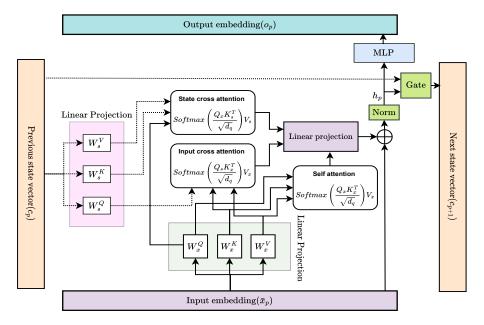


Figure 1: Comprehensive illustration of the Attentive recurrent neural network (ARNN) architecture.

channel EEG signals, that have dominantly high frequency bursts with a long-term relation in seizure classification [7, 5]. By combining local and global features, the model gains access to a rich representation of the input data, which leads to better overall detection performance. The model can learn hierarchical relationships in the data, understanding both- shortrange fluctuations (bursts of high frequencies) and overarching trends. The processing of multi-channel segments in blocks by attention layers helps in extracting interchannel features that can be memorized by LSTM-style recurrent gate and correlated with other time step vectors. The cost of recurrence in terms of both computation time, is improved compared to other baseline methods. We demonstrate empirically on heterogeneous datasets that the proposed ARNN cell performance is better than the baseline models and capable of handling lengthy sequences.

2. Related Work

Seizure detection using EEG signals has witnessed remarkable advancements with the application of deep learning techniques [8, 9, 10, 11]. In recent years, numerous studies have explored the utilization of sophisticated neural network architectures such as LSTM networks [12, 13, 6] networks and Transformers [5, 14] for enhancing the accuracy and reliability of seizure detection and prediction. This section presents an overview of recent publications that exemplify the contributions made in this direction.

LSTM networks [15, 16, 17] have shown substantial promise in capturing temporal dependencies within EEG signals, making them well-suited for seizure detection and prediction tasks. Hezam *et al.* [8] proposed a novel hybrid LSTM model that leverages both short-term and long-term EEG patterns to achieve enhanced detection accuracy. Similarly, [18] introduced a stacked LSTM architecture to capture complex rela-

tionships in EEG signals and reported improved seizure prediction performance. Another approach involves a Generative Adversarial Network (GAN) model to generate preictal data, followed by employing LSTM for classification to predict outcomes [17]. Furthermore, research has extended beyond traditional LSTMs to their variants like Gated Recurrent Units (GRUs) [16]. In [12], a comparative study of LSTMs and GRUs demonstrated the superiority of the latter in terms of computational efficiency while maintaining competitive performance in seizure detection tasks.

Recent advancements in the application of Transformers to sequential data have extended to EEG analysis for seizure detection and predictions. Recently, a lightweight Transformer architecture has been proposed to enhance accuracy in detecting seizure patterns by capturing local and global dependencies within EEG signals [5]. Similarly, [14] introduced a Multichannel Vision Transformer (MViT) for automated spatiotemporal spectral features learning in multi-channel EEG data to achieve state-of-the-art performance in seizure prediction. Researchers have also explored hybrid architectures that combine the strengths of LSTM and self-attention for classification and prediction from time-series data [13]. A recent study [19] introduced a hybrid model that employs a 1D Convolutional Neural Network (CNN) with a Bidirectional Long Short-Term Memory (BiLSTM) network to detect seizures. Convolutional tokenizer is used combined with ViT to effectively capture the temporal and spatial information in time series dataset [5, 20]. In another work [21], R-Transformer is proposed where they used LocalRNN for local dependencies in series with a selfattention mechanism to capture global dependencies. The R-Transformer used in this work enjoys both abilities but it is unable to make faster computations compared to the proposed ARNN model. In implementing the proposed architecture, the training time is significantly reduced due to the recurrent use of the attention mechanism compared to other baseline methods.

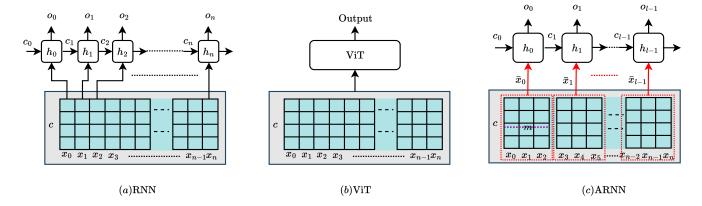


Figure 2: An illustration of sequence processing by RNN, ViT and ARNN cell. In contrast to sequential processing by RNN and parallel processing by ViT, ARNN cell operates sequentially on multi-dimensional local window of the sequence to produce global dependencies formed by local dependencies.

3. The Attentive Recurrent Neural Networks Model

The architectural framework of the Attentive recurrent neural networks (ARNN) is comprehensively described in Fig. 1. This architecture is constructed for multichannel EEG signals that can harness the advantage of attention mechanism and LSTM-style recurrent gate organized hierarchically. As shown in the figure 1, the attention layer is designed to model global structure in a multi-dimensional sequence, and gate is used to manage the context over long sequences.

3.1. ARNN cell

The process of handling data segments in a single ARNN cell is explained in this section. Let a single multi-channel EEG segment $\mathcal{X} = x_t|_{t=0}^n = \{x_0, x_1, x_2, x_3, \dots x_n\} \in \mathbb{R}^{n \times c}$ where $x_t \in \mathbb{R}^c$, c denotes the number of channels and n is the sequence length. The goal is to get the knowledge necessary to create a function that can transform the input sequence into a labels space $\mathcal{Y}: (f: \mathcal{X}^{n \times c} \to \mathcal{Y})$. This can be formulated as below,

$$y = f(x_0, x_1, \cdots x_n)$$

where is $y \in \mathcal{Y}$ is the seizure and non-seizure labels. Inherently, time-series data such as EEG, shows strong local structures. As a result, elements of construction to represent such a location are both desired and essential. The proposed architecture is designed to meet the requirement by capturing local short-term dependencies and managing them to form global dependencies.

In contrast to other efforts that typically apply RNNs to the entire sequence LSTM networks [11, 15, 17], we reconstruct the initial long sequence into numerous shorter ones, each of which contains just local information and is processed by an ARNN cell. Specifically, we create a local window of size m of the sequence that encompasses m consecutive locations and forms l local windows. Concretely, the small window $\bar{x}_p = \{x_{mp+1}, x_{mp+2}, \cdots x_{(m+1)p}\}$ of m consecutive points forms $p = [0, 1, \cdots l-1]$ local windows. The ARNN cell will learn a latent representation from the points in each local window \bar{x}_p and recurrently manage to form global long-term dependencies

of the segment x_t . Thus, the learned latent representations contain the local structure information of the long sequence. Therefore, the ARNN cell forms global dependencies by focusing on the local dependencies of local windows. Fig. 2 shows the key difference in processing a segment by an RNN, ViT, and the proposed ARNN cell.

Attention layer: Recent studies indicate that the multi-head attention mechanism proves highly efficient in capturing global dependencies by enabling direct connections between all pairs of positions [19, 20, 21]. To elaborate, within the multi-head attention mechanism, each position attends to preceding positions, generating a set of attention scores to refine its representation. Mathematically, the current local window \bar{x}_p can be processed as follows:

$$u_x = softmax \left(\frac{Q_x K_x^T}{\sqrt{d_a}} \right) V_x \tag{1}$$

Where Q_x , K_x and V_x are the query, key and value vectors of \bar{x}_p , derived from linear projection of W_x^Q , W_x^K and W_x^V weight matrices. The cross-attention helped the model to capture the interrelation between the input vector and state to concentrate on pivotal local position vectors. The effectiveness of cross-attention mechanisms is capturing interrelation across different sequences, allowing for accurate and efficient identification of seizures. Specifically, in cross-attention mechanisms, each element in one sequence attends to all elements in another sequence, generating attention scores crucial for refining its representation. The interrelation between the input vector \bar{x}_p and the state vectors c_p of the ARNN cell is formulated as follows in Eq. (2):

$$u_{xs} = softmax \left(\frac{Q_x K_s^T}{\sqrt{d_q}}\right) V_s$$

$$u_{sx} = softmax \left(\frac{Q_s K_x^T}{\sqrt{d_q}}\right) V_x,$$
(2)

Where Q_s , K_s and V_s are the state query, key and value vectors of c_p derived from a linear projection of W_s^Q , W_s^K and W_s^V

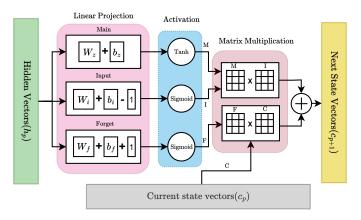


Figure 3: The ARNN cell features a distinct LSTM-style recurrent gate architecture

weight matrices. The hidden state of the cell is computed by the linear projection of concatenated vectors from u_x , u_{xs} and u_{sx} as follows in Eq. (3)

$$h_p = \left[u_x \, u_{xs} \, u_{sx} \right]^T W_o \tag{3}$$

This hidden state h_p caries the information learned from the current input \bar{x}_p and previous state vectors c_p . The normalized hidden state is used by the gate to condense the information and carry to the next state.

Recurrent Gate: We used the LSTM-style recurrent cell for gating purposes. This gate uses the standard combination of input and forgets gates as shown in Fig. 3. Although there is a separate gate for each state vector, it is allowed for their simultaneous updating. The following equation is used for the recurrent gate:

$$z_{p} = tanh(W_{z}h_{p} + b_{z})$$

$$i_{p} = \sigma(W_{i}h_{p} + b_{i} - 1)$$

$$f_{p} = \sigma(W_{f}h_{p} + b_{f} + 1)$$

$$c_{p+1} = c_{p} \odot f_{p} + z_{p} \odot i_{p}$$

$$(4)$$

The trainable weight matrices W_z , W_i , and W_f , and the trainable bias vectors b_z , b_i , and b_f are essential components of the recurrent gate. The LSTM-style gate demonstrates greater expressive power due to the dependency of f_p and i_p values on the current hidden state vectors h_p . In our model, h_p depends on c_p , thereby inducing an indirect dependency of the LSTM gate on c_p . Consequently, recurrent gate values vary across each state vector and block indices p. We incorporate a slight adjustment of -1 and +1 to the input and forget gates. This adjustment serves to initially influence the gate towards "remembering" while maintaining the scale of updates. Employing this initialization technique enables the recurrent cell to consistently leverage the recurrent state.

4. Ablation Study

Multiple time steps. The study was initiated with a robust baseline configuration, employing the ARNN cell at different time steps. Subsequent variations involved reducing the

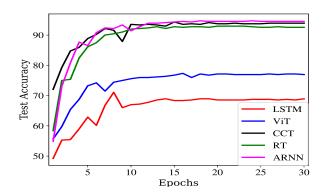


Figure 4: Testing accuracy of the proposed model against the baseline models across epochs.

time steps to 16 and 2, as well as extending them to 256. Results from the investigation demonstrated that the ARNN model achieved an accuracy of 96.37% with the lowest training time at 1024 sequence length, indicating its efficacy in capturing sentiment dynamics within the 16 time step framework, shown in figure 6. However, reducing the time steps to 8 incurred a slight decrement in accuracy to 93.52%, reflecting a discernible loss in feature richness. Further reduction to 2 time steps accentuated this effect, yielding an accuracy of 86.51% and increased the training time, indicating a substantial compromise in feature retention. Conversely, extending the time steps to 64 showcased no enhancement in accuracy to 96.35%, albeit with increased computational complexity. The findings emphasized the delicate balance between sequence length, computational efficiency, and detection performance in seizure detection tasks leveraging ARNN architectures. We conclude that the 6 time step is sufficient for the model at 1024 sequence length segment, although we did use 8 and 32 time steps depending upon sequence length.

Number of recurrent state vectors. We trained the model with differing numbers of state vectors, from 4 to 512. Initially, decreasing the number of state vectors from 512 to 64 increases the accuracy and decreases the computational time, but pro-

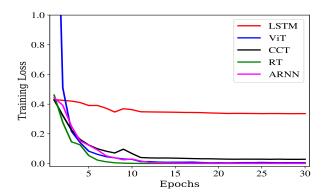
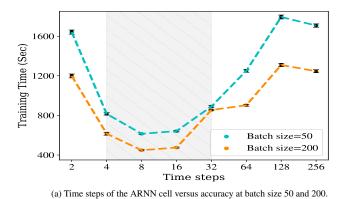
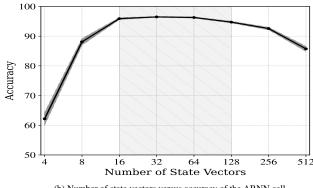


Figure 5: The evolution of training loss is compared between the proposed model and baseline models across different epochs.





(b) Number of state vectors versus accuracy of the ARNN cell.

Figure 6: An illustration depicting the effect of the (a) time step on the training time and (b) the number of state vectors on the accuracy of the ARNN cell at the segment length of 1024 of multi-channel EEG signals. The grey shadow indicates the optimal time step for the cell.

vides reasonable performance in the range of 16-64. Moreover, further decrease in the state vectors drastically decreases the accuracy and increases the training time, and worst performance with 4 state vectors (see Fig. 6b). Our conjecture suggests that the model encounters challenges in effectively leveraging the recurrent state when the state space expands or is compressed excessively.

Segment length. Decreasing the length of the segment significantly enhanced the accuracy of the ARNN model and other baseline methods as shown in Fig. 7a. However at larger segment lengths, the performance of the baseline methods decreases rapidly with increase in time complexity. However, the ARNN performance slightly deviated but the training time decreased rapidly (as shown in Fig. 7b). We hypothesized that as the segment lengthens, the architecture summarizes the information better and faster than the other baseline methods.

5. Experiments

Set-up: Experiments were run on a computer with an Apple M1 processor with 16 GB RAM, running on macOS Ventura version 13.4.1(c). The chosen batch size for training is 50, offering a balance between computational efficiency and gradient accuracy. Initially, the learning rate is set to 0.001, ensuring stable optimization of model parameters. But this rate is decreased by a factor of 0.1 at every 10 epochs to fine-tune the model convergence. The Adam optimizer is employed for its efficiency in handling sparse gradients and noisy data. Binary cross-entropy is utilized as the loss function, providing a measure of the discrepancy between predicted and actual labels. The data sets were divided into 0.75 for training and 0.25 for testing. The validation is not performed due to the small size of the datasets. The test results averages were calculated after ten iterations of each model.

5.1. Datasets

UPenn and Mayo Clinic's Seizure Detection Challenge ¹: A seizure detection challenge was organized by the National Institutes of Health (NINDS), and the American Epilepsy Society in 2014 [22]. The goal of this challenge was to facilitate the identification of specific brain regions susceptible to surgical resection in order to mitigate the occurrence of future seizures. The EEG recordings of four canines were recorded with 16 electrodes at 400 Hz, whereas human EEGs were recorded with varying electrode counts at frequency 500 or 5000 Hz. All data were divided into unbalanced 1s EEG segments and labeled as "ictal" or "interictal". This challenge sought to gain essential insights into both the shared characteristics and differences in epileptic neural activity across species by amalgamating data from diverse sources encompassing animal and human subjects. The resulting perspectives hold significant value in the enhancement of clinical interventions and the formulation of more effective treatment methods. Our model is evaluated on the labeled data of all the participants. Initially, the data is resampled at 400 Hz to make it consistent for the proposed model. The empirical findings are presented in Table 1. The ARNN demonstrates superior performance compared to the baseline models in this particular task, except slightly lagging in patients 3, 5 & 6 compared to CCT. It is hypothesized that this phenomenon arises due to the presence of pronounced intrachannel local features within the multi-channel EEG data. Although the CCT model has a multi-head attention mechanism, which is highly efficient in capturing long-term dependencies, it lacks the ability to capture local structures within sequences that could provide important features. Furthermore, the R-Transformer has demonstrated significantly superior outcomes in the case of patients 4 & 6 than the ARNN model. The computation time taken by each model is shown in the Fig. 7b, demonstrating the computational efficiency of the proposed model. Moreover, it exhibits superior performance compared to the Variational Autoencoder (VAE) by a significant margin [23]. This phenomenon can be anticipated as the attention model has a tendency to disregard the sequential information present in the local structure. Fosil et al. [24] employed the discrete log energy entropy feature and support vector machine (SVM) methodology to attain a noteworthy accuracy of 98.27%. It is worth noting that this accuracy surpasses the findings of the present work.

¹https://www.kaggle.com/c/seizure-detection

Participants	LSTM		ViT		CCT		RT		ARNN	
	Acc	f1-score								
Dog-1	0.745	0.768	0.718	0.726	0.973	0.972	0.971	0.973	0.979	0.979
Dog-2	0.869	0.917	0.894	0.907	0.981	0.982	0.978	0.978	0.982	0.982
Dog-3	0.951	0.953	0.980	0.981	0.990	0.991	0.991	0.991	0.995	0.995
Dog-4	0.934	0.947	0.959	0.959	0.977	0.978	0.984	0.984	0.986	0.986
Average	0.874	0.896	0.888	0.893	0.980	0.981	0.981	0.981	0.985	0.986
Patient-1 ^a	0.590	0.594	0.522	0.520	0.795	0.811	0.501	0.502	0.704	0.713
Patient-2	0.983	0.984	0.987	0.988	0.988	0.989	0.993	0.993	0.994	0.994
Patient-3	0.755	0.767	0.819	0.821	0.965	0.966	0.912	0.913	0.943	0.943
Patient-4 ^b	0.887	0.940	0.849	0.863	0.849	0.884	0.905	0.937	0.869	0.888
Patient-5	0.955	0.971	0.981	0.983	0.992	0.992	0.984	0.985	0.988	0.989
Patient-6	0.908	0.951	0.967	0.967	0.987	0.987	0.987	0.987	0.982	0.982
Patient-7	0.923	0.944	0.969	0.969	0.964	0.963	0.973	0.974	0.985	0.985
Patient-8	0.945	0.948	0.964	0.963	0.983	0.983	0.983	0.983	0.988	0.988
Average ^c	0.912	0.927	0.948	0.950	0.979	0.980	0.972	0.973	0.980	0.980

Excluded from average due to 174 sec available data

Table 1: A comparative analysis of accuracy and f1-score among the proposed ARNN and other state-of-the-art implemented methods on UPenn & Mayo Clinic's seizure detection challenge dataset.

However, it is important to acknowledge that their experimentation was limited to canines.

CHB-MIT²: This dataset is widely used for seizure detection and prediction work [25]. The ictal and preictal section is used by Deepa et al. [26] to identify seizures from preictal by using processing the extracted segments using the min-max normalization method. This dataset is provided to test the ability of designed model for seizure prediction. The classification performance is presented in Table 3 and compared with the previous works in Table 2. The data shown in the Table 2 indicates that, as a general trend, solely attention or recurrence-based models performance are poor compared to the ARNN model. This is because the input sequences exhibit both local and global dependencies that are required to detect seizures effectively. Thus, analyzing EEG signals for seizures is a challenge since the attention module struggles to catch local dependencies while RNN struggles to capture global dependencies in lengthy sequences. In fact, techniques that effectively capture local properties, such as Long Short-Term Memory (LSTM), provide better outcomes [27], but it fails on large segment length. We contend that this discrepancy arises due to the inherent limitation of a typical Transformer in effectively capturing local dependencies. The performance of the proposed model with other existing work is shown in Table 3. Based on the information shown in the table, it can be deduced that the CNN model suffers from a loss of temporal information, resulting in worse performance [28]. Conversely, the 1D-MobileNet model exhibits superior performance compared to the CNN model [10]. Nevertheless, our proposed ARNN model, which utilizes the self and cross-attention module recurrently, has demonstrated superior performance compared to the baseline and previous work methods.

6. Results

We tested the proposed Attentive recurrent neural network (ARNN) on two different heterogeneous datasets: CHB-MIT [29, 30] and UPenn and Mayo Clinic's Seizure Detection Challenge dataset [23, 24, 31]. The performance of the ARNN cell is also compared with baseline methods.

6.1. Comparison with baselines

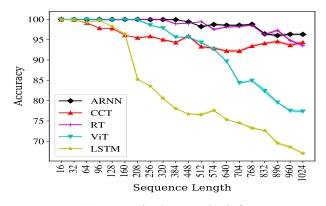
We compare the ARNN model with four different baselines. The first baseline is *LSTM* that widely used for time series data [1]. These networks excel in capturing temporal dependencies and intricate patterns across EEG channels over time, making them well-suited for tasks like EEG signal classification. However, LSTMs may suffer from vanishing or exploding gradient problems, limiting their ability to model long-range dependencies effectively [21, 6, 13]. The problem with sequence length is shown in Fig. 7, showing the training time and accuracy against the sequence length.

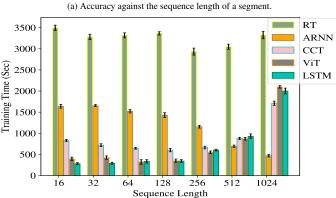
Vision Transformers (ViT): While not originally designed for EEG data [2, 32, 33], can be adapted to process multi-channel EEG segments by treating them as images. The self-attention mechanisms of ViT enable the extraction of global context across channels. However, it losses sequential information of positions and struggle with capturing fine-grained temporal dynamics [6, 13, 20]. The loss of fine-grained features leads to poor performance at larger segment lengths, as shown in Fig. 7.

Compact Convolution Transformer (CCT): It efficiently extracts spatial and temporal features from EEG data using a convolution tokenizer instead of patches in ViT [20]. It facilitates tasks like artifact removal but may overlook long-range dependencies crucial in EEG analysis. Figure 7a shows the relative performance of ViT and CCT-2/4 with learnable positional embedding, showing the capability of CCT to extract better feature than the ViT.

Excluded from average due to 210 sec available data Average performance of patients excluding 1 and 4.

²https://ieee-dataport.org/open-access/ preprocessed-chb-mit-scalp-eeg-database





(b) Time required for training with respect to the sequence length of a segment

Figure 7: Comparative analysis of the performance of ARNN and baseline models across different sequence lengths, highlighting training time and accuracy.

R-Transformer: The Recurrent neural network enhanced transformer uses the local RNN for finding the fine-grained features and transformer for global dependencies but suffers from increased complexity. Fig. 7b shows the computational time required compared to baseline methods and Fig. 7a drops in performance as sequence length increased. In this work, the R-Transformer is not implemented but used with their default value obtained form the source location [R-Transformer].

6.2. Discussion

The proposed ARNN model has been compared against four baseline approaches using various segment configurations. The ARNN model consistently achieved superior results. Table 1 provides a detailed breakdown of classification performance for each dog and human participant on the Upenn and Mayo Clinic datasets. The analysis of the table yields several key observations. Firstly, it is apparent that the self-attention-based model, despite demonstrating data parallelism, loses critical local features. Fig. 7a illustrates the effects of local features in ViT and CCT. This outcome aligns with similar observations found in the case of the CHB-MIT datasets. The Fig. 4 provides a comparative analysis accuracy against epochs of baseline methods with the ARNN models. Notably, the figure demonstrates the effects of sequence length on LSTM and loss of local features in models solely based on attention [34]. Sequential models, such

	LSTM	ViT	CCT	RT	ARNN
Accuracy	0.661	0.773	0.943	0.932	0.963
Precision	0.673	0.772	0.943	0.931	0.963
Recall	0.662	0.773	0.944	0.932	0.962

Table 2: The accuracy and micro f1-score performance parameter of ARNN with the implemented methods at 1024 segment length.

as LSTM, typically demanded more time for training and inference compared to attention-based models like ViT and CCT.

The convolution tokenizer of CCT leveraging convolutional neural networks (CNNs), efficiently dissects the EEG segment into manageable units. By sliding convolutional filters across the EEG signal, it identifies local patterns and extracts meaningful features. However, this approach has drawbacks. Firstly, CNNs lack interpretability, making it challenging to discern token generation rationale. Secondly, fixed filter sizes limit adaptability to diverse bursts of EEG. Thus, while convolution tokenizers offer robust solutions for NLP tasks, their limitations necessitate careful consideration to capture short bursts present in a segment. To overcome these issues, a recurrent neural network enhanced transformer is proposed to sequentially process the sequences of segments by local RNN [21]. This R-Transformer is complex and requires high computational time. To overcome these problems for time series data, we proposed the ARNN model, where an attention layer is applied recurrently along the sequence length. From our qualitative examination, indications suggest that the model leverages the recurrent state to encapsulate information on commonly encountered features at local locations in EEG signals. Nevertheless, it appears to lack intricate reasoning capabilities at larger time steps but demonstrated superior performance at moderate time steps on fixed segment length configuration Fig. 6. The LSTMstyle gate decides retention or dismissal based on current states and inputs, certain forms of long-range approximate attention mechanisms.

7. Conclusion

This study demonstrates the effectiveness of a novel deep learning architecture for analyzing multichannel EEG data in seizure detection tasks. Leveraging the rich source of EEG recordings from heterogeneous datasets, including the CHB-MIT and UPenn & Mayo's Clinic. The study investigates the effectiveness of novel architectures in binary class seizure detection tasks. It integrates the self and cross attention layer to extract local interchannel features in a local window of a segment recursively applied on with an LSTM-style gate. The gate recursively condenses the local features and forms global longterm dependencies. We have also shown that the larger segments are effectively processed by the proposed methods while the baseline methods fail to do that. The performance achieved by the ARNN model holds immense potential in the realm of multichannel EEG data analysis, outperforming the baseline methods. More importantly, the model achieves efficient results with less training time. The ARNN model presents an

Upen and Mayo's clinic							
Study	Year	Method	Accuracy				
İlkay et al. [23]	2022	VAE	79.00				
Nhan <i>et al.</i> [31]	2017	ACS+ Random forest	95.81				
Fosil <i>et al.</i> [24]	2020	SVM	98.27				
Nhan <i>et al</i> . [35]	2018	Integer CNN	97.10				
	-	LSTM	89.37				
Baselines	-	ViT	92.09				
Daseillies	-	CCT	97.95				
	-	R-Transformer	97.82				
Proposed	-	ARNN	98.20				
CHB-MIT							
Deepa <i>et al.</i> [26]	2022	Bi-LSTM	99.55				
Shilpa et al. [25]	2023	1D-MobileNet	98.50				
Fatima et al. [10]	2022	CCN + ML classifier	97.10				
	-	LSTM	98.19				
Baselines	-	ViT	97.82				
Dascilles	-	CCT	98.93				
	-	R-Transformer	99.80				
Proposed	-	ARNN	99.96				

Table 3: Performance comparison of ANN and baseline methods at sequence length 128 for chb-mit and 400 for upenn dataset with the state-of-the-art methods on respective datasets.

opportunity for improved accuracy, computationally efficient, and deeper comprehension in seizure detection domains. The empirical findings highlight the crucial balance between finegrained local features and global dependencies, guiding the way forward for more effective EEG-based clinical interventions.

Despite our initial accomplishments, we acknowledge that the recurrent architecture presented here has yet to reach its optimal potential. We see ample space for future research and enhancements in this field.

References

- S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, Neural Computation 9 (8) (1997) 1735–1780. doi:10.1162/neco.1997.9.8.
 1735.
 - URL https://doi.org/10.1162/neco.1997.9.8.1735 1,6
- [2] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. u. Kaiser, I. Polosukhin, Attention is all you need, in: Advances in Neural Information Processing Systems, Vol. 30, Curran Associates, Inc., 2017, 1, 6
- [3] H. Zhao, J. Jia, V. Koltun, Exploring self-attention for image recognition, CoRR abs/2004.13621 (2020). arXiv:2004.13621. URL https://arxiv.org/abs/2004.13621 1
- [4] U. Khandelwal, H. He, P. Qi, D. Jurafsky, Sharp nearby, fuzzy far away: How neural language models use context, in: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Association for Computational Linguistics, Melbourne, Australia, 2018, pp. 284–294. doi:10.18653/v1/P18-1027. URL https://aclanthology.org/P18-1027 1
- [5] S. Rukhsar, A. K. Tiwari, Lightweight convolution transformer for crosspatient seizure detection in multi-channel eeg signals, Computer Methods and Programs in Biomedicine 242 (2023) 107856. doi:https://doi. org/10.1016/j.cmpb.2023.107856. 1, 2
- [6] D. Hutchins, I. Schlag, Y. Wu, E. Dyer, B. Neyshabur, Block-recurrent transformers (2022). arXiv: 2203.07852. 1, 2, 6
- [7] S. Samiee, S. Baillet, Time-resolved phase-amplitude coupling in neural oscillations, NeuroImage 159 (2017) 270–279. doi:https://doi.org/10.1016/j.neuroimage.2017.07.051. 2

- [8] H. Albaqami, G. M. Hassan, A. Datta, Automatic detection of abnormal eeg signals using wavenet and lstm, Sensors 23 (13) (2023). doi:10. 3390/s23135960. URL https://www.mdpi.com/1424-8220/23/13/5960 2
- [9] A. T. Tzallas, M. G. Tsipouras, D. I. Fotiadis, Epileptic seizure detection in eegs using time-frequency analysis, IEEE Transactions on Information Technology in Biomedicine 13 (5) (2009) 703–710. doi: 10.1109/TITB.2009.2017939. 2
- [10] H. Fatima, F. Syed, M. Saeed, Epileptic seizure detection using a hybrid 1d cnn-machine learning approach from eeg data, Healthc Eng. (Nov 29 2022). doi:10.1155/2022/9579422. 2, 6, 8
- [11] S. Rukhsar, A. K. Tiwari, Barnes-hut approximation based accelerating t-sne for seizure detection, Biomedical Signal Processing and Control 84 (2023) 104833. 2, 3
- [12] Y. P. Singh, D. K. Lobiyal, A comparative study of deep learning algorithms for epileptic seizure classification, in: 2022 International Conference on Computing, Communication, Security and Intelligent Systems (IC3SIS), 2022, pp. 1–6. doi:10.1109/IC3SIS54991.2022.9885320.2
- [13] A. Katrompas, T. Ntakouris, V. Metsis, Recurrence and self-attention vs the transformer for time-series classification: A comparative study, in: Artificial Intelligence in Medicine, Springer International Publishing, Cham, 2022, pp. 99–109. 2, 6
- [14] R. Hussein, S. Lee, R. Ward, Multi-channel vision transformer for epileptic seizure prediction, Biomedicines 10 (7) (2022). doi:10.3390/biomedicines10071551.
 URL https://www.mdpi.com/2227-9059/10/7/1551 2
- [15] M. Varlı, H. Yılmaz, Multiple classification of eeg signals and epileptic seizure diagnosis with combined deep learning, Journal of Computational Science 67 (2023) 101943. doi:https://doi.org/10.1016/j.jocs.2023.101943. 2, 3
- [16] M. Natu, M. Bachute, K. Kotecha, hcla_cbigru: Hybrid convolutional bidirectional gru based model for epileptic seizure detection, Neuroscience Informatics 3 (3) (2023) 100135. doi:https://doi.org/10.1016/j.neuri.2023.100135.
 URL https://www.sciencedirect.com/science/article/pii/S2772528623000201 2
- [17] S. M. Usman, S. Khalid, Z. Bashir, Epileptic seizure prediction using scalp electroencephalogram signals, Biocybernetics and Biomedical Engineering 41 (1) (2021) 211–220. doi:https://doi.org/10.1016/ j.bbe.2021.01.001. 2, 3
- [18] A. Pandey, S. K. Singh, S. S. Udmale, K. Shukla, An intelligent optimized deep learning model to achieve early prediction of epileptic seizures, Biomedical Signal Processing and Control 84 (2023) 104798. doi:https://doi.org/10.1016/j.bspc.2023.104798. 2
- [19] I. Ahmad, X. Wang, D. Javeed, P. Kumar, O. W. Samuel, S. Chen, A hybrid deep learning approach for epileptic seizure detection in eeg signals, IEEE Journal of Biomedical and Health Informatics (2023) 1– 12doi:10.1109/JBHI.2023.3265983. 2, 3
- [20] A. Hassani, S. Walton, N. Shah, A. Abuduweili, J. Li, H. Shi, Escaping the big data paradigm with compact transformers (2022). arXiv:2104. 05704. 2, 3, 6
- [21] Z. Wang, Y. Ma, Z. Liu, J. Tang, R-transformer: Recurrent neural network enhanced transformer (2019). arXiv:1907.05572. 2, 3, 6, 7
- [22] W. C. bbrinkm, sbaldassano, Upenn and mayo clinic's seizure detection challenge (2014). URL https://kaggle.com/competitions/seizure-detection 5
- [23] İlkay Yıldız, R. Garner, M. Lai, D. Duncan, Unsupervised seizure identification on eeg, Computer Methods and Programs in Biomedicine 215 (2022) 106604. doi:https://doi.org/10.1016/j.cmpb.2021. 106604.
 - URL https://www.sciencedirect.com/science/article/pii/S0169260721006787 5,6,8
- [24] F. O. K, R. R, Automatic detection of naturally occurring epilepsy in dogs using intracranial electroencephalogram signals, Procedia Computer Science 171 (2020) 91-100, third International Conference on Computing and Network Communications (CoCoNet'19). doi:https://doi. org/10.1016/j.procs.2020.04.010. URL https://www.sciencedirect.com/science/article/pii/ S187705092030973X 5.6.8
- [25] I. V. Taon, H. M. Taon, T. M. Lo, T. T. M. Huyanh, H. T. Taon, C. V. T.
- [25] L. V. Tran, H. M. Tran, T. M. Le, T. T. M. Huynh, H. T. Tran, S. V. T.

- Dao, Application of machine learning in epileptic seizure detection, Diagnostics 12 (11) (2022). doi:10.3390/diagnostics12112879. URL https://www.mdpi.com/2075-4418/12/11/2879 6, 8
- [26] B. Deepa, K. Ramesh, Epileptic seizure detection using deep learning through min max scaler normalization, International journal of health sciences 6 (S1) (2022) 10981–10996. doi:10.53730/ijhs.v6nS1.7801. 6,8
- [27] X. Qiu, F. Yan, H. Liu, A difference attention resnet-lstm network for epileptic seizure detection using eeg signal, Biomedical Signal Processing and Control 83 (2023) 104652. doi:https://doi.org/10.1016/j. bspc.2023.104652.6
- [28] S. SJ, R. Mehta, S. Vityazev, K. K. Singh, Epileptic seizure prediction using 1d-mobilenet, in: 2023 25th International Conference on Digital Signal Processing and its Applications (DSPA), 2023, pp. 1–5. doi: 10.1109/DSPA57594.2023.10113426.6
- [29] S. Rukhsar, Y. Khan, O. Farooq, M. Sarfraz, A. Khan, Patient-specific epileptic seizure prediction in long-term scalp eeg signal using multivariate statistical process control, Irbm 40 (6) (2019) 320–331. 6
- [30] A. H. Shoeb, Application of machine learning to epileptic seizure onset detection and treatment, Ph.D. thesis, Massachusetts Institute of Technology (2009). 6
- [31] N. Truong, L. Kuhlmann, M. R. Bonyadi, J. Yang, A. Faulks, O. Kavehei, Supervised learning in automatic channel selection for epileptic seizure detection (2017). arXiv:1701.08968. 6, 8
- [32] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, N. Houlsby, An image is worth 16x16 words: Transformers for image recognition at scale (2021). arXiv:2010.11929. 6
- [33] A. K. Gupta, R. Kumar, L. Birla, P. Gupta, Radiant: Better rppg estimation using signal embeddings and transformer, in: 2023 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), 2023, pp. 4965–4975. doi:10.1109/WACV56688.2023.00495.6
- [34] E. Tsironi, P. Barros, C. Weber, S. Wermter, An analysis of convolutional long short-term memory recurrent neural networks for gesture recognition, Neurocomputing 268 (2017) 76–86, advances in artificial neural networks, machine learning and computational intelligence. doi:https://doi.org/10.1016/j.neucom.2016.12.088.7
- [35] N. D. Truong, A. D. Nguyen, L. Kuhlmann, M. R. Bonyadi, J. Yang, S. Ippolito, O. Kavehei, Integer convolutional neural network for seizure detection, IEEE Journal on Emerging and Selected Topics in Circuits and Systems 8 (4) (2018) 849–857. doi:10.1109/JETCAS.2018.2842761.