Towards low power cognitive load analysis using EEG signal: A neuromorphic computing approach

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Abstract

Real-time on-device cognitive load assessment using EEG is very useful for applications like brain-computer interfaces, robotics, adaptive learning etc. Existing deep learning based models can achieve high accuracy, but due to large memory and energy requirement, those models can not be implemented on battery driven low-compute, low-memory edge devices such as wearable EEG devices. In this paper, we have used brain-inspired spiking neural networks and neuromorphic computing paradigms, that promises at least 10^4 times less energy requirement compared to existing solutions. We have designed two different spiking network architectures and tested on two publicly available cognitive load datasets (EEGMAT & STEW). We achieved comparable accuracy with existing arts, without performing any artifact removal from EEG signal. Our model offers $\sim 8\times$ less memory requirement, $\sim 10^3\times$ less computational cost and consumes maximum 0.33 μJ energy per inference.

1 Introduction

Cognitive load (CL) is the amount of mental workload experienced by an individual while performing a task [Sweller, 1988]. User performance is dependant on the CL experienced by him/her. Excessive CL might lead to conditions such as stress/anxiety [Soto and Humphreys, 2008], depression [Wenzlaff and Bates, 1998], elevated heart rate [Galy et al., 2012], loss of attention/engagement level [Berggren et al., 2013] etc. leading to degradation in performance. However, an optimum amount of CL is required to successfully perform the task [Sweller, 1988]. Thus, assessment of CL is important and add value in various application areas such as human behavior analysis [Aldayel et al., 2020], brain-computer interfaces (BCI) [Jeunet et al., 2016], adaptive learning [Moos, 2013] etc. To do so in out-of-the-lab scenario, CL computation need to be done in real time and on device.

Various physiological changes, controlled by sympathetic and para-sympathetic nervous system, like cardiovascular changes [Singh et al., 2019], galvanic skin resistance [Das et al., 2016], eye movements [Gavas et al., 2017], have been used for assessment of CL. However, most reliable assessment is done using brain signals captured via functional magnetic resonance imaging (fMRI) [Whelan, 2007], functional near infra-red imaging (fNIR) [Broadbent et al., 2023] and Electroencephalogram (EEG) [Das et al., 2013], [Gavas et al., 2016]. EEG measures the electrical activity of our brain using electrodes placed on the scalp. It is relatively easier to use and cheaper compared to fNIR or fMRI. Thus, attempts have been made to use EEG based measurements in real life scenarios. EEG band powers like theta, alpha and beta band powers, reflect the CL [Chatterjee et al., 2021], [Gavas et al., 2016]. For problem solving task, researchers have used alpha power and asymmetry in alpha band as features [Jaušovec, 2000]. Literature suggest that theta activity in hippocampus area is associated with cognitive performance [Kahana et al., 2001]. Various machine learning and deep learning approaches have been used in studies for assessment, classification and prediction of CL. In an early study [Gevins et al., 1998], authors used neural networks for EEG signal pattern recognition for various workloads

37th Conference on Neural Information Processing Systems (NeurIPS 2023).

and achieved an average accuracy of 90% for the same. In another study [Friedman et al., 2019], authors used variety of machine learning approaches to predict problem difficulty. They reported that XGBoost classifier outperform all other classifiers. In another study [Bashivan et al., 2015b], authors used wavelet and spectral features along with support vector machine for CL classification. They also tried deep belief networks and reported an accuracy of 92% while executing memory tasks. Recently, researchers used representation learning [Bashivan et al., 2015a], deep recurrent neural networks [Kuanar et al., 2018], and few other deep learning architectures [Saha et al., 2018] as well.

Deep learning based architectures offer better classification accuracy compared to machine learning models but they require large volumes of data for training and learning the feature representation. Additionally, more accurate and high performance models involve large number of network parameters, which in turn calls for more complex computations and power consumption. Moreover, EEG signals are highly susceptible to various artifacts like muscle artifacts, blink artifacts, movement artifacts, jaw movements etc. Thus, noise removal is a necessary step in EEG signal processing which also calls for additional computations. Thus, it is still a challenge to use EEG for real time CL analysis on wearable EEG devices itself.

Recently, Spiking Neural Networks (SNNs), a next-gen ML framework [Ponulak and Kasinski, 2011], has been developed inspired by functionalities of neurons and synapses of mammalian brain. SNNs run on non-von Neumann Neuromorphic Computing (NC) platforms such as Intel Loihi [Lin et al., 2018], Brainchip Akida [bra, 2019] etc. and are capable of low power computations using sparser data. Thus, these are an eligible candidate for implementing machine intelligence at battery driven edge devices (like robots, wearable etc.) that have low compute resource. Features such as (i) event based asynchronous data processing in form of spikes, (ii) collocation of memory and compute in spiking neurons, and (iii) natural ability of temporal feature extraction, makes SNN-NC combo to be inherently very low-power & low-compute approach particularly fit for CL analysis on wearable EEG devices.

In this paper, we have analyzed the performance of SNN for CL analysis and its possibilities to be implemented on wearable devices. To the best of our knowledge, this is the first attempt for EEG-based CL analysis using SNN. We have designed two SNN architectures (namely feed-forward and recurrent) and tested on two open datasets - EEGMAT and STEW, via 5-fold cross validation method and Leave-One-Subject-Out (LOSO) method. We observed that feed-forward SNN has achieved 70% & 79% accuracy for LOSO on these two datasets respectively. Our model have $\sim 8\times$ less memory requirement, $\sim 10^3\times$ less computational cost compared to SoA and consumes maximum 0.33 μJ energy per inference. We have also compared performance of our method with few prominent approaches suggested in literature such as [Ramaswamy et al., 2021], [Siddhad et al., 2022], [Pandey et al., 2020], [Attallah, 2020]. Our results are particularly encouraging in three ways:

- in our proposed approach artifact removal is not required which in turn reduces overall computational complexity.
- high accuracy in LOSO method ensures robustness of the system and its high generality across subjects.
- most of the existing NC boards supports feed-forward architecture only - thereby making our model a good candidate for real life implementation.

2 Methodology

In this section, we will describe the datasets used and the SNN architectures that we have designed.

2.1 Dataset description

We have used two publicly available datasets, namely *MIT-PhysioNet EEGMAT* [Zyma et al., 2019] and *Simultaneous Task EEG Workload* (STEW) [44r, 2018] in the present work.

EEGMAT dataset contains artifacts free signals of 36 subjects performing mental arithmetic task. EEG signals were recorded using 23-channel EEG device (sampling frequency 500 Hz.) for 3 minutes of resting state and 1 minute of task period. The participants were divided into *Group "B"* and *Group "G"* based on their performance. 12 participants belonged to *Group "B"*, who faced difficulty in performing the task. Remaining 24 participants belonged to *Group "G"*.

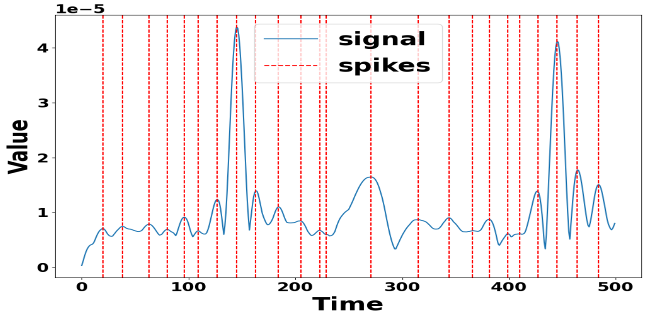

Figure 1: Peak-based spike encoding of EEG signal

STEW dataset contains raw signals of 48 subjects for SIMKAP multitasking test [Bratfisch et al.]. The signals were captured using 14 channel Emotiv device (sampling frequency of 128 Hz). EEG data was acquired for 2.5 minutes with subjects at rest. Next, subjects performed the SIMKAP test and the final 2.5 minutes were used as the workload condition. Subjects rated their perceived CL after each segment of the experiment on a scale of 1-9.

2.2 Data Preparation

EEGMAT contains artifacts free EEG data and STEW dataset contains EEG data with artifacts. Artifacts removal is a compulsory step for EEG analysis. However in our proposed approach this step is not required and we have used the signals as is. EEG recordings measure the difference in electrical potential of each electrode with respect to a reference electrode. To represent voltage in each of the channels with respect to another electrode, we re-referenced the channels. This new reference can be any particular channel, or the average of a channels. We have used the average of a channel as reference. Next, we detected the peaks in this re-referenced signal using the NeuroKit toolbox [Makowski et al., 2021]. Thus, we get a train of spikes for a EEG signal. Next, a window of length w sec are selected which are then used to train the SNN network. We have experimented with various window sizes to see its effect on performance. To mitigate the class imbalance problem in both the datasets, we have down sampled the EEG data.

2.3 Proposed Network Architecture

The system workflow and SNNs are depicted in Fig. 2. SNNs mainly comprises of: spiking encoder, spiking network and a classifier. Details of each block is given below.

Spike Encoding: Any real-life analog data, such as EEG signal, need to be converted into a train of events, aka spikes, because SNNs can work on events or spikes only. The spikes carry the signal information to other neurons in the network. The information may be coded via the number of spikes or via inter-spike interval. In this work, we have detected the peaks of all the re-referenced EEG channels and considered them as spikes. This way, the spike train retains the temporal pattern of the EEG signal. A representative diagram of a single EEG channel and corresponding spike train are depicted in Fig. 1.

Spiking Networks: We have tried two SNN architectures - one is recurrent (in the form of reservoir) and another is feed-forward. Recurrent network is expected to capture the temporal signature of EEG signal better, whereas, the feed-forward network is easier to implement on NC platforms. Below we discuss both:

- ***Reservoir:*** The reservoir is a set of excitatory and inhibitory spiking neurons that are recurrently connected. The inter-neuron synaptic connectivity however is sparse, probabilistic and remain within the same population to ensure dynamical stability of the network. This kind of recurrently connected set of neurons are very efficient in extracting spatio-temporal features from temporally varying signals such as EEG. Recurrent weights with directed cycles do play the role of a non-linear random projection of the sparse input feature space into a higher dimensional spatio-temporal embedding - and that helps generating explicit temporal features.

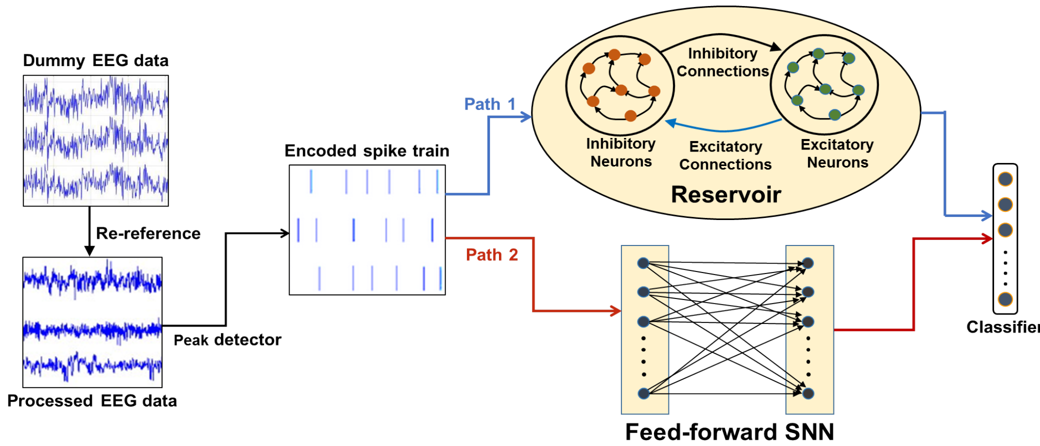

Figure 2: Architecture Diagram

- ***Feed forward:*** It is a simple network topology where the spiking neurons connected across consecutive layers but usually there is no intra-layer connection. In our case, we have used full connectivity between layers. Once the input spike train is fed into the network, these connections learn via Backpropagation rule. Since the spikes are non-differentiable, an arctan surrogate gradient was used to approximate the heaviside function representation of a spike [Neftci et al., 2019]. Post training, the network captures the learned features in neuronal activities and synaptic weights.

More details about both the architectures and different parameters used in them can be found in [Dey et al., 2022]. We have used the ***Leaky-Integrate and Fire (LIF)*** [Ponulak and Kasinski, 2011] neuron model to implement aforesaid SNNs. LIF is computationally easier to simulate and work with compared to other neuron models such as Izhikevich, McCulloch-Pitts etc. [Hayman, 1999, Izhikevich, 2003]. In LIF model, the membrane potential of a neuron decays according to its temporal dynamics and is incremented with the incoming inputs. If the membrane potential of a neuron crossed a certain fixed threshold, the neuron emits a spike. After spiking, a neuron goes into a refractory period and in this period, the neuron does not receive any incoming data and acts as a dead neuron. LIF neuron model is described by Eqn. 1 .

$$\begin{aligned} \tau_m \frac{dV}{dt} &= (V_{rest} - V) + IR \\ s &= \begin{cases} 1, & V \geq V_{thresh} \\ 0, & V < V_{thresh} \end{cases} \end{aligned} \tag{1}$$

In this equation, V is the neuron membrane potential that varies with the input stimuli and when it crosses a threshold, V_{thresh}, the neuron emits a spike s. V_{rest} is the resting membrane potential, I represents the total input current to the neuron from all its synapses. R is the total resistance encountered by I during synaptic transmission. Without any input, V exponentially decays with a time constant τ_m.

Classification:

We have used a sigmoid function on the membrane potentials of output layer neurons to get the final classification results. In our case the number of output neurons always corresponds to number of classes available for the task in hand.

3 Experimental Results & Discussion

We have designed and simulated above mentioned spiking networks via snnTorch - a PyTorch based SNN simulator [Eshraghian et al., 2021]. A tool called RayTune [Liaw et al., 2018] has been used for hyper parameter tuning. For our experiments, different sets of network parameters were used. Among those sets of network parameters, the optimal set was found using a grid-search method [Shekar

Table 1: Network parameters for the experiments

Dataset	Reservoir					Feed-Forward	
	No. of excitatory neurons	No. of inhibitory neurons	Input Outdegree	Weight Scalar	τ_m	No. of feed forward neurons	τ_m
EEGMAT	4000	1000	500	(2.0, 1.7, 0.9, 0.1, 1.4)	15	2000	20
STEW	5000	1000	500	(2.0, 1.4, 0.3, 0.7, 1.1)	25	4000	30

and Dagnew, 2019] using RayTune. The parameter values used for both reservoir and feed-forward network architectures are listed in Table 1.

With these optimal set of parameters, we have executed two different types of testing methodologies - (a) Classical *5-fold cross validation (5-FCV)* and (b) *Leave-One-Subject-Out (LOSO)*. In the 5-FCV method, training and testing was performed using 80-20 split. As mentioned in Section 2.1, EEGMAT has two classes while STEW has three classes. We have used window size w = 1, 2 and 4 seconds for both the cases (refer Section 2.1). Below, we summarize the results in details.

Table 2: Performance of Reservoir Architecture (using 5-FCV) [1] : [Ramaswamy et al., 2021], [2] : [Siddhad et al., 2022]

Dataset	Accuracy (%)		SOP
	SoA	Proposed Approach	
EEGMAT	95 [1]	70	8
STEW	88 [2]	64	25

Table 2 reports the performance of the Reservoir network on both the datasets using 5-FCV testing methodology and a window size of 2 seconds. We achieved less accuracy compared to state of the arts (SoA). Moreover, the computational cost is found to be high for Reservoir. To understand the computational cost quantitatively, we have taken *Synaptic Operations (SOP)* as a metric. Usually, number of SOP is considered as the average number of spikes per timestep for the entire training and inference and more spikes means more computation. The last column of Table 2 shows the estimate of SOP per timestep for both the datasets. Due to recurrent connections between large number of neurons in the reservoir (refer Table 1), large number of SOP was observed in the network resulting into higher computation cost and processing time.

Table 3 reports performance of feed-forward network for both 5-FCV and LOSO methods with respect to different window sizes. It is observed that the classification accuracy varies with window size. Window size = 2 seconds provides the best performance - 75% & 86% (5 FCV) and 70% & 79% (LOSO) classification for EEGMAT and STEW respectively. Respective F1 scores are also reported in the table. For EEGMAT, a smaller window size (1 second), degrades the performance for both LOSO and 5-FCV, whereas increasing window size from 2 seconds to 4 seconds degrades LOSO performance but does not affect much for 5-FCV. For STEW, degradation is observed for both the cases.

Table 4 reports the performance comparison between existing SoA and feed-forward SNN. Clearly for LOSO testing method, our model performs better with respect to the LSTM based approach [Pandey et al., 2020] and at par with SVM-KNN based approach [Attallah, 2020]. For 5-FCV, our model performs at par for STEW dataset compared to a transformer based architecture [Siddhad et al., 2022]. For EEGMAT the accuracy is less compared to that reported in [Ramaswamy et al., 2021], which used a combination of topographic map generation and Conv-LSTM model. LOSO being a more generic and acceptable testing method, our method seems fit for practical applications.

However, the real benefit of using SNN comes when computational effort and energy consumption are being compared. As can be seen from Table 4, our feed-forward SNN models have 50K training parameters which is $\sim$7.5x less than that used in [Ramaswamy et al., 2021] - thus providing huge

Table 3: Performance of Feed-Forward Architecture

Dataset	Window size (w) (second)	Input spikes per window of EEG data	Feed Forward SNN			
			5-FCV		LOSO	
			Accuracy	F1 score	Accuracy	F1 score
EEGMAT	1	22	68	0.73	60	0.63
	2	**45**	**75**	**0.76**	**70**	**0.72**
	4	92	75	0.74	55	0.56
STEW	1	25	84	0.84	77	0.77
	2	**52**	**86**	**0.87**	**79**	**0.80**
	4	104	80	0.79	71	0.71

Table 4: Performance comparison between our proposed method and existing prior arts with respect to accuracy, computational effort and power consumption. [1]: [Ramaswamy et al., 2021], [2]: [Siddhad et al., 2022], [3]: [Pandey et al., 2020], [4]: [Attallah, 2020]

Dataset	Accuracy (in %)				Training Parameters		Computation Effort		Approx. Power consumption	
	5-FCV		LOSO							
	Our	Others	Our	Others	Our	Others	Our	Others	SOP	Energy (μJ)
EEGMAT	75	95 [1]	70	74 [4]	50K	3.7M [1]	o(10^3)	o(2×10^4)[4]	3	0.243
STEW	86	88 [2]	79	62 [3]	68K	55K [3]	o(7×10^2)	o(9×10^5)[2] o(4×10^4)[3]	16	0.331

benefit in terms of memory and power requirement. As per [Mohammadi Farsani and Pazouki, 2020], the computational cost of transformer based EEG classifiers (such as [Siddhad et al., 2022]) are $o(n^2\times d)$ where n is the length of input sequence and d is the input dimension (here, number of EEG channels). On the other hand, the same for SNN is $o(s\times d)$ where s is the total number of input spikes. For the case of STEW, n = 2x128, d = 14 and s = 52 for window size = 2 (refer Table 3). Consequently, the computational cost of [Siddhad et al., 2022] is approximately $o(9\times10^5)$ and that for [Pandey et al., 2020] is $o(4\times10^4)$ while same for feed-forward SNN is $o(52\times14) \approx o(7\times10^2)$, i.e. our model provides a benefit in the range of 10^2 to 10^3 times. Similarly, for EEGMAT, d = 23 and s = 45, so computational cost of feed-forward SNN here is $o(45\times23) \approx o(10^3)$, whereas that for [Attallah, 2020] is $o(2\times10^4)$ i.e. 20 times more than ours.

Energy requirement of an SNN is directly proportional to total number of synaptic operations (SOP) executed during runtime. As mentioned earlier, SOP is inherently dependent on the total number of spikes produced by the model, which includes the input spikes as well as the spikes occurring in the subsequent SNN layers during run-time. For example, during experiment with EEGMAT dataset, we observed a total number of spikes = 3000 on an average per sample data of window size 2 seconds. This 3000 spikes included the 45 input spikes (refer column 3 of Table 3) and the spikes (≈2955) in feed-forward SNN layer. So we can calculate SOP as 3000/(2×500(sampling rate)) = 3. Similarly for STEW, SOP is found to be 16. Using this SOP values and the power consumption figures for Intel Loihi neuromorphic chip [Davies et al., 2018], we have calculated approximate power consumption in microJoule per inference which is pretty low and fits the power budget of wearable EEG devices.

4 Conclusion

In this paper, we have presented an application of SNN and NC for real time in-situ cognitive load assessment using EEG signal targeted towards implementation on wearable EEG device. We have shown that the proposed method works without artifact removal from the signal and works best for LOSO validation mode. The model has very low memory and energy footprint making it eligible for implementing on battery driven EEG devices. In future, we want to test the model on few more EEG dataset to prove its robustness and implement it on real neuromorphic hardware such as Intel Loihi, Brainchip Akida etc.

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