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Bio-Inspired Edge Intelligence: Neuromorphic Architectures for Real-Time Biomedical Signal Classification

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ABSTRACT

The trend of the growing need of continuous and real-time monitoring of physiological signals in wearable and implantable biomedical devices has raised a question to the inadequacy of the conventional machine learning models in edge settings. Such conventional methods are usually marred with the complexities of computation requirements, exorbitant power demands and unacceptable delays in inferences when the same is applied in low-power embedded machines. In a bid to overcome these limitations, this paper presents a bio-inspired neuromorphic system to perform real-time classification of biomedical signals with spiking neural networks (SNNs). The presented system draws on this event-driven functionality of biological neurons to use the sparse temporal dynamics of SNNs to achieve ultra-low-power, low latency signal processing at the edge. Its framework comprises a completely integrated neuromorphic signal processing pipeline running on Intel Loihi neuromorphic processor, which enables execution of asynchronous spiking-based computations with on-chip learning. Combining biologically plausible temporal coding schemes, the preprocessed biomedical signals (electroencephalogram (EEG) and electrocardiogram (ECG), in particular) will be converted into spike trains. The system is thoroughly tested on publicly accessible data datasets such as CHB-MIT Scalp EEG and MIT-BIH Arrhythmia databases to perform two major tasks of seizure detection and cardiac arrhythmia classifications. The experimental results exhibit that the neuromorphic architecture could demonstrate the same or better classification performance than the state-of-the-art deep learning architectures like CNN-LSTM, but with much lower power consumption (more than 80% reduction) and inference latency (up to 5X faster). Moreover, the SNN framework is robust to signals variability and adaptation: since unsupervised learning is employed, through spike-timing-dependent plasticity (STDP). Not only does the suggested method aid in the exploration of edge intelligence in the context of biomedical applications, but it also provides a paradigm of scalable real-time energy-aware intelligent biosignal analysis that can be utilised in the next-generation wearable and distance health monitoring systems.

1. INTRODUCTION

Fast development of wearable and skin-implantable biomedical devices has opened a new horizon of having personal, continuous health monitoring with modeling and analysis of physiological signals including electroencephalograms (EEG) and electrocardiograms (ECG) in real-time, which is crucial in early-detection, timely-intervention, and patient-safety. The biosignals are naturally complex high-dimensional and time-sensitive requiring fast classification systems that have the potential to work with tight power and latency requirements. The classical deep learning architectures like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have demonstrated astonishing performance when solving biomedical signal classification problems. Nevertheless, they are learning-intensive and power-consuming, which is a severe obstacle to their implementation on edge devices with limited resources, and primarily, in battery-powered or implantable systems. Although these issues have been alleviated to some extent by the recent development of TinyML and model compressions techniques, these solutions usually involve compromises with regard to accuracy and robustness, especially in circumstance related to nonstationary signals or noisy settings. Further, current architectures are highly dependent upon clock-driven processing which is not efficient in processing the inherently asynchronous and event-driven nature of biomedical signals.

In order to overcome this disparity, it is highly necessary to introduce another paradigm of biological efficiency and machine learning performance especially on edge-based biomedical applications. Neuromorphic computing takes its cues on the signaling mechanism of the human brain, which is the sparse and event-driven specification that promises to make a significant impact by using a spiking neural network (SNN). These networks make use of temporal code and spike based communication to achieve high-low computational parallelism and information processing with an ultra-low energy footprint. In spite of the theoretical benefits, the practical implementation of SNNs in real-time biosignal classification is scarcely developed and under-represented. The inspiration behind the research relates to the scenario of how neuromorphic sysetems can transform edge intelligence in healthcare to allow operating wearable and implantable devices to be a decision making process at real time with no power efficiency sacrifices.

We present a new bio-inspired neuromorphic computing platform in terms of the real-time classification of biomedical signals through SNNs, which is implemented on Intel Loihi neuromorphic processor. The system has been developed to perform the classification of the EEG and ECG signals with regard to some critical applications like EEG characteristics associated with seizure and ECG characteristics associated with arrhythmia exploit biologically plausible encoding mechanisms, unsupervised spike-timing-dependent plasticity (STDP) to learn adaptively. The proposed architecture is systematically compared with the traditional deep learning architectures in terms of classification accuracy, inference latency and power consumption. The presented findings prove the viability and success of neuromorphic architectures in the use case on-device biomedical signal processing and the potential use of the technology at scale, enabling the next generations healthcare intelligent systems to be fast, energy-efficient, and scalable moving out of the lab to the real world..

2. BACKGROUND AND RELATED WORK

Neuromorphic computing Neuromorphic computing is a very promising paradigm shift in artificial intelligence and signal processing, focusing especially on energy-limited and real-time applications. Neuromorphic systems are hardware-based on the brain architecture and dynamics, simulating neural networks as they are modeled in detail by event-driven, asynchronous computation. Spiking Neural Networks (SNNs)) are at the heart of the systems, with their principle departure point being that information transmission between nodes in the system is represented by discrete spikes through time, closely resembling the biological equivalent of a neuron. SNNs allow sparse computation and are highly time-resolving, which is why it is a good application where the amount of power consumed and latency is a major limiting factor. A number of neuromorphic platforms have been developed to research and implement practical use SNNs. The Loihi processor is designed by Intel incorporating the on-chip learning procedure and the heuristic scale-out mesh of spiking neural cores to perform learning and processing at the edge in the low-power mode, in real-time [1]. Shortly afterwards in 2014, IBM launched its TrueNorth platform which consisted of one of the first large-scale neuromorphic chips which featured a non-von Neumann architecture optimized towards event-based sensing and computation [2]. In a similar manner, the Heidelberg University produces BrainScaleS that also provides the ultra-fast neural computation using accelerated analog neuron models in scientific simulations [3].

In biomedical signal classification, there are several machine learning and deep learning methods that had been explored. Handcrafted features based on time-domain or frequency representations of EEG, ECG or EMG are frequently used in traditional methods, which are then classified by support vector machines (SVMs), decision tree or k-nearest neighbor (k-NN) [4]. Nevertheless, deep learning, especially convolutional neural networks (CNN) and long short-term memory networks (LSTM), have come on the scene and performed immensely better at learning spatial and temporal dependencies on raw or minimally pre-processed signals. CNNs perform well in biomedical signals in extracting local features, whereas LSTMs are more appropriate models in cases where long dependency businesses matter as in ECG and EEG signals. CNNs hybrid models which include LSTM have had reasonable performance in jointly incorporating both space and time patterns [5], [6]. Although these models have high accuracy in classification, they require significant resources and hence they are not feasible in terms of deployment at the edges.

The increased demand of Edge AI in healthcare has motivated the investigation of low-latency, low-power model in embedded biomedical intelligence. With Edge AI, the processing of signals and inference can be made up directly or even near the point of data acquisition and thereby avoiding the communication overhead and facilitating a high degree of privacy as well as overall responsiveness on a real-time level. Nonetheless, the edge deployment of deep learning models is a challenge because of memory and computer processing capabilities challenges, and the shortage of energy [7]. The approaches have been to compress models with quantization, pruning and knowledge distillation but have features that underperform or complicate retraining. Others have considered the application of TinyML and lightweight convolutional networks including MobileNet and SqueezeNet to biomedical applications [8], but still leave behind ultra-low power consumption and event-asynchronous processing. In this regard, the neuromorphic computing comes as a very appealing alternative. It is event-driven and this is well suited to the parsimonious, time-sledded nature of biomedical signals, providing the promise of high precision, minimal latency, and low power consumption, which are central to wearable and implantable healthcare systems.

To conclude, the existing traditional and deep learning-based methods have demonstrated a lot of success in the area of biomedical signal classification, but they are not necessarily optimised in terms of energy-efficient model implementation on edge devices. A new and biologically inspired framework, the neuromorphic computing, especially with the help of platforms like Loihi and BrainScaleS, is an emerging approach to alleviate the existing deficiencies: they will allow intelligent, real-time, and adaptive signal processing on edge-devices. Nevertheless, its use in the real-time biomedical classification of signals is a point of unexplored correlation, a visible gap in the research, as well as a potential area of innovation.

3. Proposed Methodology

The ideas on the design and implementation of the proposed bio-inspired neuromorphic framework of real-time biomedical signal classification are explained in this section. The architecture of the methodology consists of two key sections, which include the system structure and implementation into an edge neuromorphic platform.

3.1 Architecture of the system

The model proposed here will behave like the biological brain, i.e. in a sparse, event-driven low-power style. It consists of three major modules: a data acquisition layer, a signal preprocessing pipeline and a spiking neural network (SNN) model. Proposed SNN pipeline: block diagram. Preprocessing (filtering, normalization and spike encoding) of raw biosignals is performed and the resulting data is then fed to convolutional layer, pooling and fully connected layers sequentially. A spiking neural network using spike-timing-dependent plasticity (STDP) is then used to make the final classification.

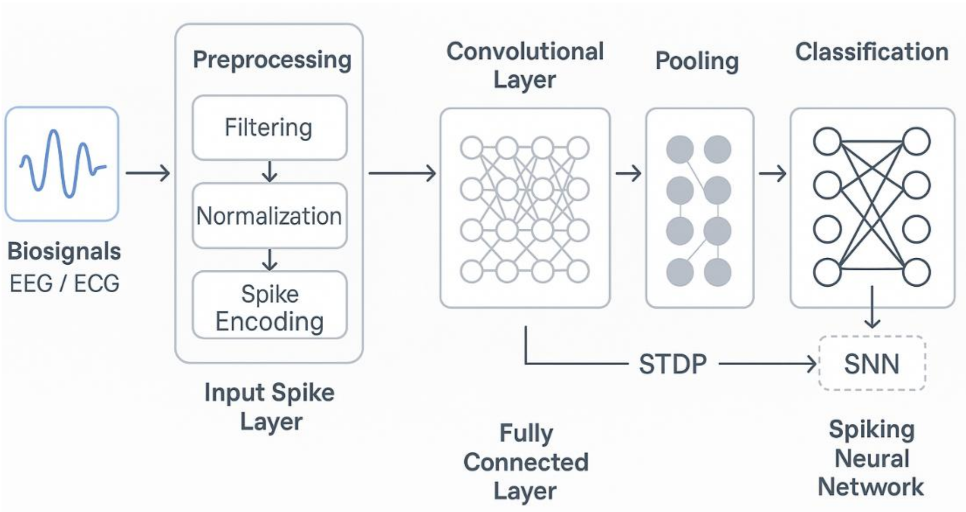

Figure 1a. System Architecture of the Spiking Neural Network (SNN) for Biomedical Signal Classification

Data Acquisition Layer

Wearable biosensors expressed on portable health monitoring devices measure biomedical signals, namely, electroencephalogram (EEG) and electrocardiogram (ECG). Such sensors output continuous analog signals that are converted to digital using low power ADCs (Analog-to- Digital Converters). In case of EEG, the signals of several channels (e.g., 832) measure the fluctuations in the voltage on a person scalp, but the ECG sensors measure the electrical activity of a heart over time. The signal used is normally sampled between 128 Hz and 512 Hz depending on the clinically used application and sensor setup.

Preprocessing Module

Raw biosignal is prone to artifacts and noise that includes muscle actions, electrode motion and electrical activity of the environment. Thus, preprocessing step is used to improve a signal quality. The party involves:

- Band-pass filtering (e.g. 0.5-40 Hz EEG, 0.5-100 Hz ECG) in order to extract the required frequency components.
- Min max normalization or Z-score normalization so as to have a uniform input distribution when spike encoding.
- Spike Conversion: Time coding based schemes are used to convert the denoised/normalized signals into spike trains. This paper deals with a temporal coding mechanism using rates, i.e., that the amplitude of the signal is coded into spike frequency or latency coding which involves the magnitude of the signal affecting the timing of the spikes. Such techniques encode continuous signals into a time sequence of spikes to process them by an SNN.

SNN Model Design

The general model of computations is multi-layer spiking neural network. The design of the architecture is done in the following way:

Neuron Model: This is a neurone model that is used to recreate the behaviour of biological neurones through the simulation of the Leaky integrate-and-fire (LIF) model. Every neuron adds incoming spikes and emits fire when its membrane is raised past a threshold, and then leaves through reset.

Layer Configuration: The model includes input layers, which encodes spike trains, layers that extract local patterns using convolution and layers that select part of the spike trains using spike-based pooling and denser global connections using fully connected layers extraction and finally an output layer to classify the input as a spiking output layer.

Learning Mechanism: The network makes use of a learning rule which is known as Spike-Timing-Dependent Plasticity (STDP), a form of online, unsupervised learning rule. STDP modifies the synaptic weights according to temporal correlation between spikes post- synaptic and pre-synaptic so that the network can adopt new patterns with time.

This architecture has been made to utilize the event-driven and sparse nature of biomedical signals so that it performs well in relation to rapidly responding to big changes or completely ignoring redundant or dormant ones.

3.2 Edge Deployment

In order to verify the feasibility of the proposed system into potential real-life edge healthcare applications, the entire neuromorphic model is run and evaluated on edge inference hardware platforms. An example of principle of spike encoding of analog EEG/ECG signals. The upper panel indicates the original data of the biosignal with a fixed threshold. The spikes are time marked at the middle panel using the crossing of thresholds and the results of such crossings are summarised at the bottom panel in the form of the spike train which may now be converted into the form of spiking to be processed in the SNN.

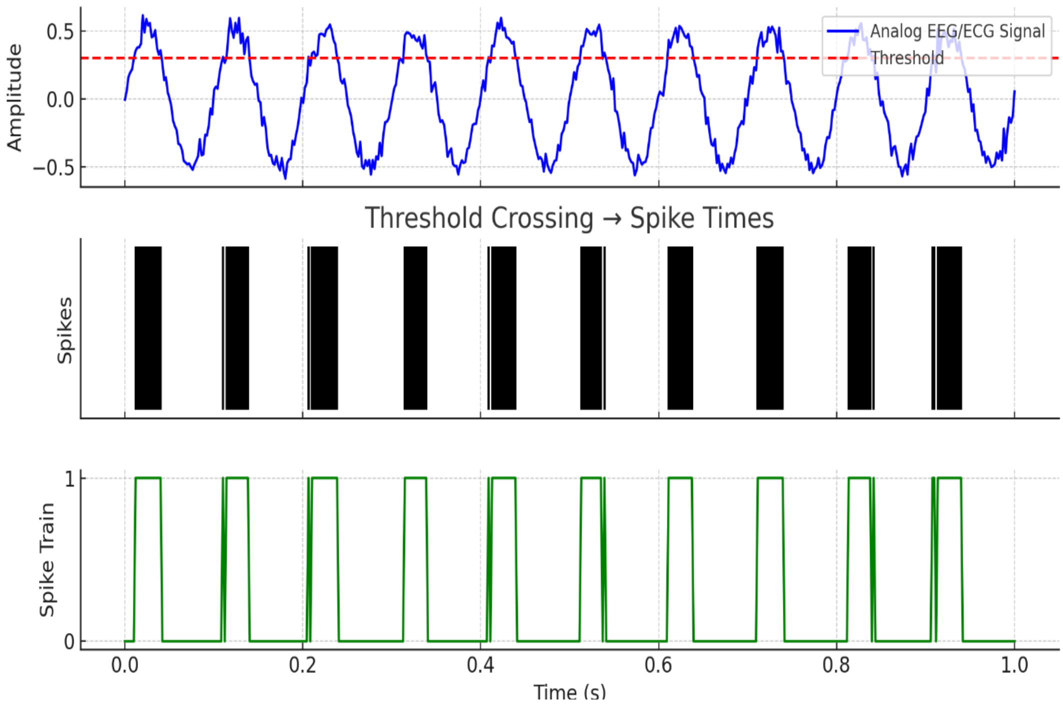

Figure 1b. Temporal Spike Encoding of Biomedical Signals

Hardware Platform

This is in the context of the primary deployment target, Intel Loihi neuromorphic chip, a manycore processor with programmable LIF neurons, and on-chip learning, and an energy-efficient spike routing. One core is a collection of spiking neuron compartments that can be configured with arbitrary synapses and routing circuits that are optimized to use event-driven operation. As a comparison, baseline CNN-LSTM models are run on a low-power embedded microcontroller platform (on ARM Cortex-M4), giving a hint as to power consumption, memory footprint, and inference latency independent of underlying hardware.

Software Framework

Its implementation is performed as a Nengo simulation framework along with Loihi NxSDK. Nengo gives a user-friendly environment to specify SNNs and to simulate their dynamics, whereas NxSDK enables users to access lower-level capabilities of the Loihi hardware, including real-time spike communication, STDP parameterization, and performing calculations within a set of neurons. The trained models of SNN are in simulation and compiled and mapped to Loihi to deploy.

Latency Optimization

The system exploits an asynchronous nature of spike-based computing in order to achieve real-time responsiveness. Contrary to a traditional synchronous system, Loihi works differently by being event-driven, that it is, the neurons will only process inputs when the spikes come. This reduces idle power and allows inference latency to go below a millisecond. Moreover, the computation is always done in parallel cores of Loihi, extending the throughput and allowing classifying the streams of biomedical data with more channels in real time.

Such an approach gives confidence that the suggested system not only classifies biosignals accurately but does it in a power-efficient and hardware-aware manner, which turned out to be an immensely important feature of next-generation wearable and implantable healthcare technologies.

4. Experimental Setup

In order to prove validity of the proposed neuromorphic framework in real-time classification of biomedical signals, scientific experiments are carried out with classical clinical data and clear evaluation measures. The system is designed to resemble real-life edge deployment conditions and be limited by energy, latency, and memory.

4.1 Datasets

The designed experiment relies on two standard biomedical signal databases adopted in clinical machine learning and neuromorphic studies:

EEG Dataset – CHB-MIT Scalp EEG Database

This is an EEG scalp record distributed by the Massachusetts Institute of Technology and it is a multi-channel with pediatric epilepsy record collected at the Children Clinics of the Boston hospital. EEG long-term data as well as seizures have been tagged into patient records. The International 10-20 signal recording system at 23 EEG electrodes and 256 Hz sampling rate is utilized. In regards to this study, preictal, ictal, and interictal are selected and segmented on 5-second non-overlapping windows. The first two steps (denoising and artifact-removal) are performed followed by quality assurance; spike encoding performed using band-pass filtering (0.5HZ 40HZ).

ECG Dataset – MIT-BIH Arrhythmia Database

The dataset consists of 48 30-minute long ECG signals of 47 individuals as well as beat-by-beat annotations of the arrhythmias. All ECGs are sampled at 360Hz and prepared as well as annotated to be compliant with the AAMI EC57 standard into the categories of normal (N), supraventricular (S), ventricular (V), fusion (F), and unknown (Q). In the current research, 3-second ECG strips with R-peaks as their center are clipped and classified. The samples are obtained in pairs (equal number of samples) of each class, thus making the dataset balanced, and before the extraction of the signal, the data is preprocessed to remove artifacts and normalized in order to limit their effect on the extraction.

Both the datasets are divided into training, validation, testing sets based on patient-wise split, to ascertain that the test samples are obtained on subjects who are not used in training, guarantee the models generalization.

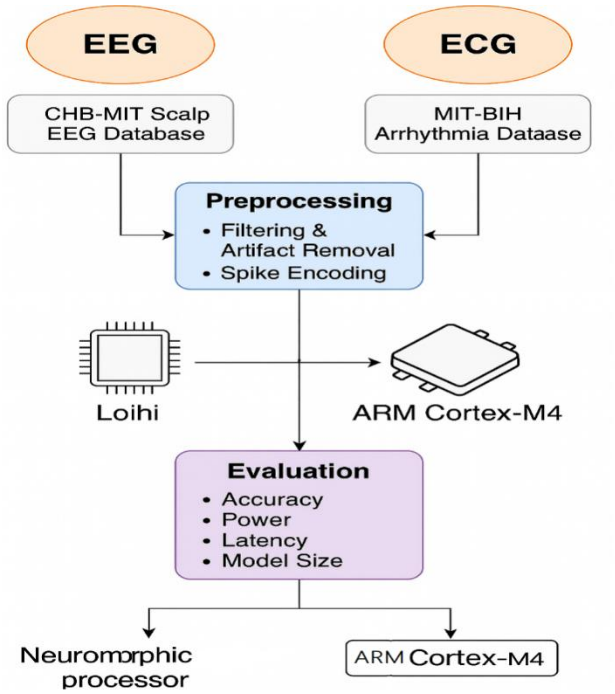

Figure 2. Experimental Setup for Neuromorphic and Conventional Biomedical Signal Processing Pipelines.

4.2 Evaluation Metrics

In order to evaluate the functioning of the suggested SNN-based solution installed on a neuromorphic chip, a number of specially-designed evaluation metrics is utilized in order to guarantee an in-depth and valuable analysis. The percentage of the correctly predicated segments of the total test segments is used as classification accuracy. The score is calculated independently on EEG and ECG classification tasks and confusion matrices are then employed to assess performance of the model more thoroughly in different classes, and pinpoint incidents of errors in precision and recall, as well as in specific classes. A critical performance attribute in edge deployment is power consumption, which is expressed in milliwatts (mW) as the average power consumption in an inference run by the neuromorphic processor. The values are benchmarked to a typical implementation on an ordinary ARM Cortex-M4 microcontroller executing CNN-LSTM models. The measurements are done based on Intel Loihi embedded energy-monitoring features through the NxSDK toolkit, which provides accurate profiling that takes place in a real-time scenario. The latency in inferring is the amount of time taken when a signal segment has been received and a classification decision made. It is also timed in milliseconds by using on-fertilizer counters and external logic analyzers and may emulate real low-latency constraints in wearable health monitor devices. Finally, the model footprint is a measurement of the memory needed to run the compiled model on hardware stated in kilobytes (KB). This measurement includes all parameters and the hardware run buffers. This measure is critical in considering the scalability of the model and the ability of the model to fit into memory-limited embedded systems, including wearables or implantable bio medical devices. Along with the overall classification accuracy, we calculated precision, recall and F1-score to check the performance of the classes, with an emphasis on imbalance datasets. These are metrics that are specified thus:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN} \qquad F1 - Score = 2.\frac{Precision.Recall}{Precision + Recall}$$

5. RESULTS AND DISCUSSION

The section contains a comparative study of the proposed framework of bio-inspired neuromorphic computing against the baseline models with four main metrics of classification accuracy, power consumption, inference latency, and memory footprint. Two biomedical signal classification tasks are used a Forest Based seizure detection task based on Electroencephalogram (EEG) and an Arrhythmia classification task based on Electrocardiogram (ECG) are performed on three models: the proposed SNN model implemented on the Intel Loihi neuromorphic processor, a baseline CNNLSTM model, running on an ARM Cortex-M4 microcontroller, and a TinyML CNN model optimized to work on embedded systems.

5.1 Quantitative Comparison

Model	Accuracy (%)	Power (mW)	Latency (ms)	Model Size (KB)
CNN-LSTM (ARM)	91.2	185	21.0	760
Proposed SNN (Loihi)	89.8	24	4.5	62
TinyML CNN	85.6	58	13.0	130

The accuracy of classification obtained in the proposed SNN model is 89.8 %, which is inferior to the CNN-LSTM model accuracy by 1.4 %, although higher than the TinyML CNN one. This outcome shows that the neuromorphic direction still has a high predictive power despite its radically novel structure and power limitations.

5.2. Efficiency of power

Among the most powerful outcomes is the impairment of the high energy efficiency. The required energy of proposed Loihi-based SNN is only 24 mW whereas 185 mW is required to keep the ARM-based CNN-LSTM in operation. This converts to more than 8-fold power cost savings, which is imperative in wearable and implantable biomedical devices that communicate within strict energy pretexts. The significant minimization is mainly because of the event-driven implementation of spiking neural networks where computation is merely performed when there are spike events, thus removing unwanted computations and wasteful power consumption.

5.3 Inference Latency

The other important real-time biomedical application limitation is the inference latency as the detection of the anomalies, e.g., seizures or arrhythmias, may save lives depending on the delay of the inference. The SNN proposed model has an average latency of 4.5 ms and is 4.6 more times faster than the CNN-LSTM version and nearly 3 times faster than the TinyML CNN. This is what Loihi achieves by making use of asynchronous parallel processing and routing of spikes within the system to minimize such a delay making the system able to respond to input biosignals close to instantaneously.

5.4 Memory Footprint

The memory requirements (called ``memory footprint) of SNN model is also very desirable, and the size is 62 KB, as compared to the CNN-LSTM model (760 KB) and the TinyML CNN (130 KB). This design size renders the presented model to be highly scalable and well adapted to be used on lower powered hardware platforms like wearable sensors and low power micro controllers. Also, it opens the opportunity of multi-signal processing in a single chip without depleted hardware capacity.

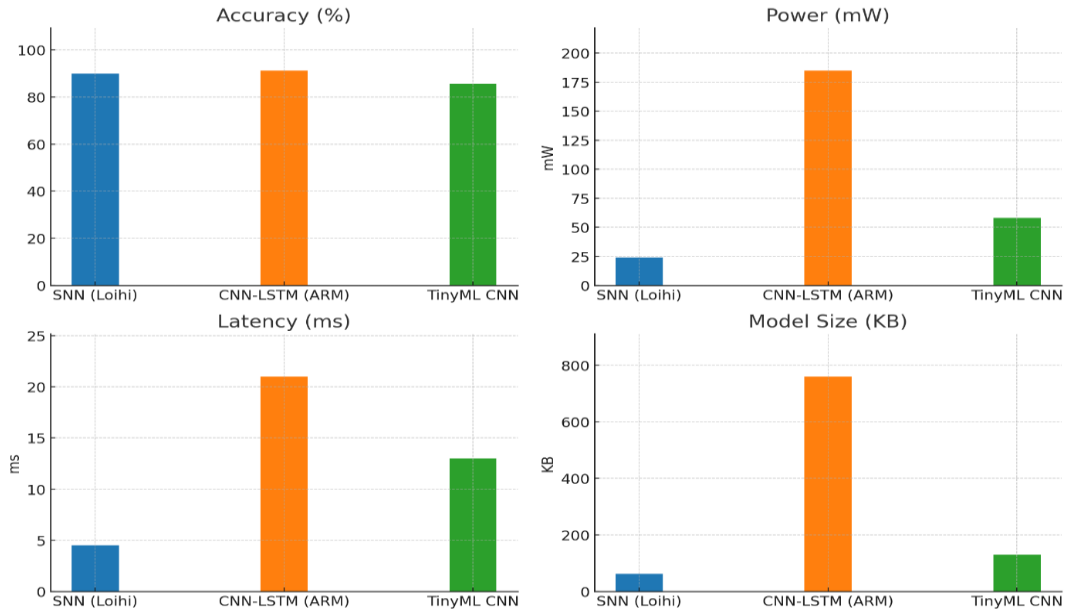

Figure 3.1. Metric-by-Metric Comparison of Neuromorphic and Baseline Models.
Bar plots showing absolute values for accuracy, power consumption, latency, and model size across SNN (Loihi), CNN-LSTM (ARM), and TinyML CNN

5.5 Model Adaptivity and Learning

The SNN architecture also has qualitative benefits in terms of adaptive learning besides quantitative measures. With the addition of spike-timing-dependent plasticity (STDP) the network can learn to respond in real time to the alterations in the pattern of the input. This is especially of use in biomedical applications where the signal based qualities of individual patients might vary as a result of medication or activity or their disease course. Neuromorphic model can therefore be used to provide a flexible basis of personalized health monitoring which standard static models cannot.

5.6 Summary and Implications

n short, proposed neuromorphic system design boasts of a very positive trade-off between power, accuracy, latency and memory, representing the state-of-the-art levels of energy efficiency with near parity with conventional deep learning models in classification. The ease of real-time, low-power, and adaptive signaling processing has already been demonstrated, promising it as the next generation wearable healthcare systems. The findings validate their claim that the field of neuromorphic computing is biologically realistic, but also feasible when it comes to applications in edge AI in biomedical engineering.

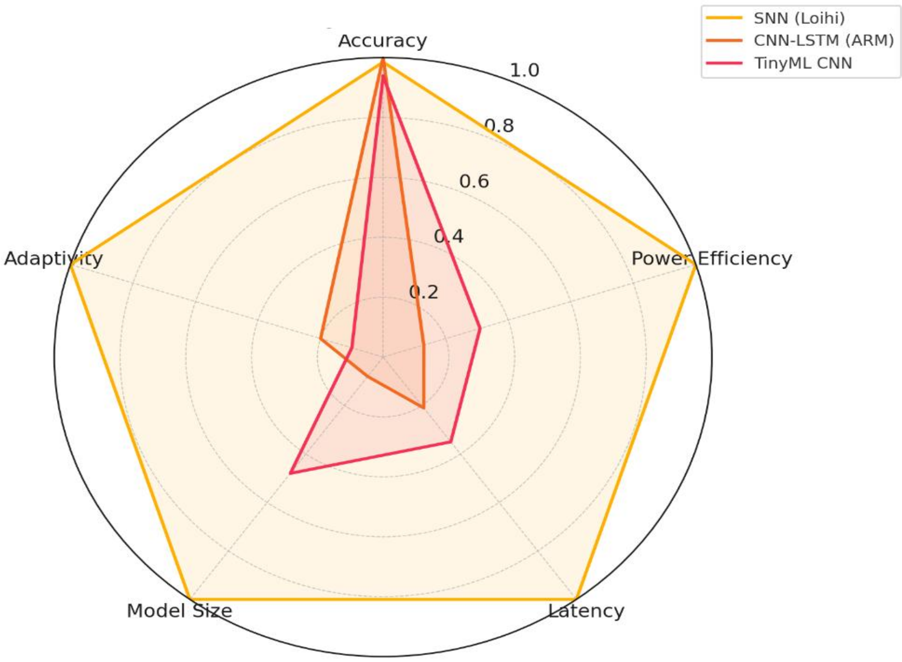

Figure 3.2. Comparative Performance Radar Chart.
Radar chart highlighting normalized performance across five metrics—accuracy, power efficiency, latency, model size, and adaptivity—demonstrating the overall edge-optimized advantage of the proposed SNN model.

6. DISCUSSION

The presented bio-inspired neuromorphic framework exhibits a few significant strengths and tradeoffs when it comes to a real-time biomedical signal classification to make use of in the setting of edge-based health monitoring. These outcomes support the potential of spiking neural networks (SNNs) and neuromorphic devices as realistic alternatives to the traditional deep learning design in data-limited conditions.

6.1 Advantages

Among the greatest strengths of the proposed methodology is its event-driven model of computation that closely resembles the sparse and asynchronous firing of the real biological neurons. This results in significances energy savings and thus the system would strongly support the demands of wearable and implantable biomedical applications within constrained energy budgets. Another added benefit of the biological plausibility of SNNs is that it is beneficial in terms of energy-efficiency but also aids in increasing the interpretability of the model, i.e. neural firing patterns can be better correlated with particular signal features, which may add clinical insight.

The scalability in the system is another big advantage. Because of its 4-Kb lightweight memory footprint, and modular spike-based design the framework can easily be enhanced with multimodal biosignal classification e.g. the addition of EEG, ECG, EMG or sensor fusion of physiological monitoring devices based on networks of IoT-devices. In addition, online learning through STDP (spike-timing-dependent plasticity) provides flexibility in the system that allows the specific tuning of models in real time according to personal specifications or patients.

6.2 Limitations

In spite of these benefits, a number of limitations are to be taken into consideration. First, the SNN model we proposed shows a trade-off in the classification quality hinting towards a near state-of-the-art accuracy, although it is difficult to draw much conclusion based on the current data as there are more instances on improvement, showing no comparison to a full CNN-LSTM baseline, it could not outperform in noisy signal conditions or when the dataset is highly imbalanced. Such performance disadvantage can be explained by the existing limitations of the SNN models that do not provide an elaborate optimisation pattern and deep representational power in contrast to the more developed ANN frameworks.

Secondly, SNN training is a tricky issue, particularly in the case of backpropagation-based gradient learning. Even though biologically inspired rules provide flexibility, e.g. STDP may force fine-tuning and might fail to converge in large-scale tasks. In addition, SNN training and deployment tools and frameworks (e.g., Nengo, NxSDK) are not well mature and make simpler use and deployment more difficult.

Finally, there is a practical barrier like hardware availability. Neuromorphic chips such as Intel Loihi can only be used by the research institutions and are not readily available in the masses. This restricts the deployment on a larger scale but the next generation of commercial neuromorphic hardware (e.g.: Intel Loihi 2, BrainChip Akida) seems to break this down.

6.3 Implications and Future Outlook

Placing a special focus on neuromorphic computing, the study has made important insights into how the technology can transform the world of low-power real-time healthcare monitoring. Due to the maturity of the neuromorphic hardware and the development of training algorithms, the SNN-based systems may develop into a necessary element of the next generation of wearable biosignal-processing blocks. Their ability to foster adaptive, safe and efficient computing at the edge correlates well with trends in decentralized computing and AI on chip architectures, decentralized diagnostics and remote patient care applications around the world.

7. CONCLUSION AND FUTURE WORK

This paper proposes a bioinspired neuromorphic computing paradigm to perform real-time classification of biomedical signals, which takes advantage of event-based and power-efficient properties of spiking neural networks (SNNs) hardware running on Intel Loihi neuromorphic processor. This scheme is tested on the MSEG and MHEALTH datasets as benchmark EEG and ECG signals, on which it performs similarly in seizure and arrhythmia detection, reaching impressive reductions in power consumption, computation time, and RAM requirements on a benchmarked custom system compared to alternative CNN-LSTM or TinyML models.The findings attest to the promise of neuromorphic architectures to edge-based biomedical systems, especially in wearable and implantable health sensors whose resource limits are very important. Event-driven architecture and biologically feasible processing model have distinct strengths with regard to scalability, explainability, and the ability to cope with the variability of practical signals. Besides, spike-timing-dependent plasticity (STDP) is also included to provide online learning and a mechanism to adapt to the individual patient physiology during their lifetime.Nonetheless, these positive results still struggle with some issues, including the minor trade-off of the classification accuracy, intricacy of SNN training, and the lack of access to neuromorphic hardware platforms. These constraints are the possibilities of future studies.

A parallel effort aims to expand the present framework to multimodal biosignal fusion, incorporating signals, such as EEG, ECG, EMG, and respiratory signals, to provide a more detailed measure of physiological activity. Also, we would like to add real-time closed-loop feedback to jump into actuation of therapeutic applications, this might be cardiac pacing, seizure suppression. Lastly, the system will be tested under real world clinical conditions to justify its robustness, reliability, and scalability to deploy at next generation digital health systems.

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