# Machine-Learning-Powered Neural Interfaces for Smart Prosthetics and Diagnostics

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Abstract—Advanced neural interfaces are transforming applications ranging from neuroscience research to diagnostic tools (for mental state recognition, tremor and seizure detection) as well as prosthetic devices (for motor and communication recovery). By integrating complex functions into miniaturized neural devices, these systems unlock significant opportunities for personalized assistive technologies and adaptive therapeutic interventions. Leveraging high-density neural recordings, on-site signal processing, and machine learning (ML), these interfaces extract critical features, identify disease neuro-markers, and enable accurate, low-latency neural decoding. This integration facilitates real-time interpretation of neural signals, adaptive modulation of brain activity, and efficient control of assistive devices. Moreover, the synergy between neural interfaces and ML has paved the way for self-sufficient, ubiquitous platforms capable of operating in diverse environments with minimal hardware costs and external dependencies. In this work, we review recent advancements in AI-driven decoding algorithms and energy-efficient System-on-Chip (SoC) platforms for next-generation miniaturized neural devices. These innovations highlight the potential for developing intelligent neural interfaces, addressing critical challenges in scalability, reliability, interpretability, and user adaptability.

Index Terms—Neural Interfaces, Neuromodulation, Brain-Computer Interfaces (BCI), Machine Learning, System-on-Chip.

#### I. INTRODUCTION

Modern neural interfaces can simultaneously record thousands of neural signals [1]. This capability generates massive volumes of data that demand efficient processing and compression to extract meaningful insights [2]–[4] (Fig. 1(a)). Furthermore, advances in neural interface technology have enabled real-time recording and transmission, paving the way for high-resolution mapping of brain activity [5], [6]. However, the scale and complexity of neural data pose significant challenges in processing, storage, and interpretation, necessitating innovative approaches in both hardware and software.

Machine learning (ML) has emerged as a transformative tool for data analysis, enabling the execution of sophisticated tasks that were previously unattainable. ML algorithms excel at identifying patterns in complex datasets, making them invaluable for applications such as brain-computer interfaces (BCIs) aimed at motor and communication restoration [7]–[10]. Additionally, ML facilitates therapeutic applications, including mental state recognition, migraine detection, and seizure prediction [11]–[15]. Moreover, brain-triggered neuro-modulation systems leverage ML to adaptively modulate brain

activity in response to disease-specific neuromarkers, offering personalized and precise therapeutic interventions [5], [16], [17].

To achieve these advanced functionalities, integrating neural interfaces and ML into miniaturized systems has become a key research focus [16], [18]–[22]. Existing works have demonstrated promising results in developing energy-efficient system-on-chip (SoC) platforms for real-time neural signal processing and decoding. However, significant challenges remain in achieving hardware efficiency, ensuring scalability, and maintaining the reliability and interpretability of these systems. Addressing these challenges is essential for advancing next-generation neural interfaces that combine compact designs with robust performance in real-world applications.

## II. NEURAL INTERFACES

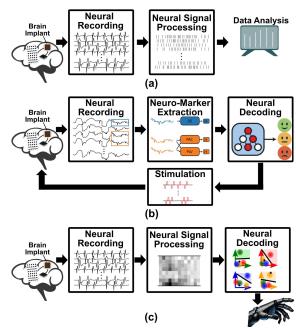


Fig. 1. **Neural Interfaces:** (a) Neural recording interfaces capture high-density neural signals and process them to reduce data rates, or wirelessly transmit them to an external computer for further processing. (b) Therapeutic neural interfaces extract neuro-markers to detect disease-related neurological symptoms or mental states, and may also integrate neurostimulation for functions such as seizure suppression or brain rewiring. (c) Prosthetic neural interfaces use ML to convert brain intention into actionable commands, enabling control of end-effectors like robotic hands.

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Diagnostic/Therapeutic Applications— ML can empower advanced therapeutic devices and transform the diagnosis and treatment of neurological and psychiatric disorders, enabling real-time monitoring, adaptive neurostimulation, and personalized interventions (Fig. 1(b)). These systems enhance clinical outcomes and patient independence via seizure/tremor suppression, emotion regulation, and migraine therapy. By integrating real-time detection of neurological symptoms (e.g., seizures) with closed-loop neuromodulation, these devices deliver targeted stimulation to prevent seizures [5], [16]. Similarly, closed-loop neural interfaces can be used to treat tremors in patients with Parkinson's disease by detecting and modulating abnormal oscillations [5], [17]. Neural interfaces are also being applied in the treatment of psychiatric disorders, for example, in decoding emotional and anxiety-related states, analyzing connectivity and spectral dynamics to guide adaptive neurostimulation and biofeedback therapy [12], [22], [23].

Prosthetic/Assistive Applications— Prosthetic neural interfaces employ ML to decode brain signals in order to drive a wide range of effectors, enabling brain control of prosthetic limbs and communication devices for individuals with disabilities (Fig. 1(c)). Such interfaces provide critical functionalities such as artificial limb movement [24], locomotion assistance through wheelchair operation [25] and direct activation of natural limbs via neuromuscular [26] or spinal cord stimulation [10], facilitating the restoration of walking and hand movements. Also, neural prostheses empower individuals to perform daily tasks, including communication through cursor control and typing [27], writing [8], and speaking [9]. Recent advancements in BCIs emphasize greater task complexity and dexterity, including high-degree-of-freedom control and ability to distinguish diverse actions [9], [28]. These systems are paving the way for groundbreaking applications, ranging from cognitive enhancement tools to advanced assistive technologies that adapt to the user's needs, delivering unprecedented functionality and adaptability [29], [30].

## III. MACHINE LEARNING FOR NEURAL INTERFACES

ML techniques, including traditional and deep learning (DL) models, have transformed neural data analysis by uncovering hidden brain patterns while enhancing real-time neural decoding, brain function modeling, and feature-level interpretability.

# A. Traditioinal Machine Learning

Traditional ML models, including linear, tree-based, and probabilistic methods, are widely used in neural signal processing, neurological symptom detection and motor decoding. Distance-based techniques and window discrimination offer computational efficiency, memory savings, and real-time processing, making them well-suited for neural interfaces [5], [31]. Methods such as K-means and window discrimination classify data by proximity to centroids, shown to be efficient solutions in simple ML tasks, such as spike detection and sorting [31], [32]. K-Nearest Neighbors (KNN) is a non-parametric, flexible method suited for emotion recognition and early seizure detection, adapting to individualized neural

activity [33], [34]. It offers low-complexity training without weight optimizations, but can be computationally expensive during inference on large datasets [35].

Linear Discriminant Analysis (LDA) maximizes class separability while reducing dimensionality, offering an interpretable and low-complexity solution for motor decoding [20]. Support Vector Machines (SVMs) effectively decode neural signals, with linear SVMs performing well in simple tasks and kernel SVMs handling complex applications like seizure detection. While SVMs provide efficient inference and low memory usage, the training complexity increases with data size. Alternatively, Gradient Boosted Decision Trees (GBDTs) excel in non-linear, high-dimensional neural data modeling, making them effective for cognitive state classification and seizure detection [12], [18], [36]. They use hierarchical decision rules, reducing computational overhead and hardware complexity, while requiring minimal memory to store tree structures and split thresholds [37]. GBDTs offer high interpretability, enabling neuro-marker identification and providing clear decision paths for neural decoding analysis. Hidden Markov Models (HMMs) and Kalman Filters (KFs) enable sequential neural decoding through probabilistic modeling, iteratively updating hidden states (e.g., motor intentions) by estimating the most probable state based on observed neural data [10], [38]. This self-recalibration capability makes them well-suited for real-time neural decoding in adaptive BCIs.

#### B. Deep Learning

Traditional ML models potentially offer real-time and compute-efficient solutions for neural interfaces but typically struggle to capture non-linearities within high-dimensional datasets. DL addresses these limitations by automating feature extraction and modeling temporal, spatial, and global neural representations efficiently [8], [9], [13]. DL's adaptability makes it essential for complex neural decoding and adaptive BCIs, albeit with increased computational complexity.

Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are essential for temporal modeling in neural decoding [8], [9]. RNNs capture long-term dependencies, aiding in motor decoding and seizure detection, while CNNs extract localized temporal patterns for efficient processing. Unlike sequential RNNs, CNNs enable parallelized operations, reducing latency and computational cost for real-time BCIs and neuroprosthetic control, whereas RNNs enhance long-range temporal understanding. Graph Neural Networks (GNNs) model spatial dependencies in neural signals, advancing mental regulation and seizure classification [13], [39]. For example, residual state update mechanism (REST) efficiently captures spatiotemporal dependencies in EEG, enabling realtime seizure detection with significantly reduced computation and memory [13] (Fig. 2(a)). Transformers address longrange dependencies in motor decoding using Multi-Head Self-Attention, enhancing emotion recognition and cross-subject generalization in movement decoding [40], [41]. Though computationally demanding, their parallelized processing enables real-time applications with optimized architectures. Attention maps further improve interpretability by identifying key neural features for decoding.

## C. Feature Engineering

Feature engineering plays a crucial role in neural data analysis (decoding and processing), as it enhances scalability and interpretability. It reduces data dimensionality to enhance computational efficiency while extracting informative features for better interpretation of neural activity. A recent study introduced a lightweight, robust framework that utilizes common neuro-markers—such as spectral energy (SE), line length (LL), phase-amplitude coupling (PAC), phase-locking value (PLV), correlation, and band power ratio between channels (BPRC)—for decoding anxiety-related behaviors, leveraging SHapley Additive exPlanations (SHAP) to quantify feature importance and identify key features [12]. SHAP analysis highlighted high- $\gamma$  spectral and connectivity features as key neuro-markers for decoding defensive behaviors in local field potentials (LFPs) recorded from the infralimbic cortex (IL) and basolateral amygdala (BLA) of rats (Fig. 2(b)). Selecting high-SHAP features preserved decoding accuracy while significantly reducing dimensionality and latency, making the method efficient for real-time, low-power neural decoding in implantable neuropsychiatric systems. Alternatively, the Distinctive Neural Code (DNC) algorithm employed a class saliency metric to compute feature importance and extract the most distinctive features (Fig. 2(c)) [21]. This approach simplified the decoding task, achieving high accuracy with a low-complexity classifier such as LDA.

# IV. NEURAL SYSTEMS-ON-CHIP

Over the past decade, numerous efficient ML and signal processing techniques have been developed, particularly for on-chip spike detection and sorting. For example, adaptive spike detection methods dynamically adjust parameters using adaptive thresholding and nonlinear energy operator (NEO) transformations to enhance sensitivity [43], [44]. Spike sorting SoCs incorporate various clustering and classification techniques along with feature extraction strategies (e.g., fixed geometric features and salient feature selection) yielding improvements in both accuracy and computational efficiency [31], [32]. More advanced neural interface SoCs integrate AI for sophisticated therapeutic and prosthetic applications, enabling real-time adaptation and enhanced functionality.

## A. Neural SoCs for Diagnostic/Therapeutic Applications

Therapeutic devices must make robust, low-latency decisions while providing real-time feedback (e.g., neurostimulation). Thus, accuracy and latency are particularly critical in applications such as seizure detection and mental regulation [11]. One such example is a closed-loop device designed to restore motor function following brain injury by re-establishing lost connectivity between cortical areas [45]. It detects premotor cortex action potentials and promptly triggers somatosensory cortex stimulation, facilitating recovery. However, this system

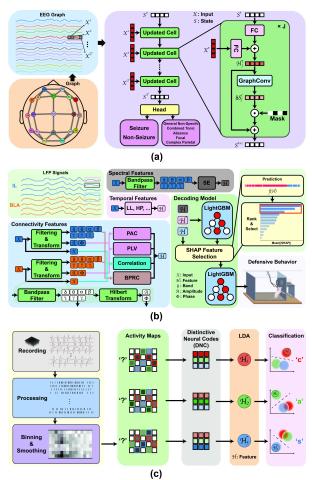


Fig. 2. Efficient ML Models for Neural Decoding: (a) Residual State Updates (REST) for seizure detection [13]. (b) Light Gradient-Boosting Machine (LightGBM) and SHapley Additive exPlanations (SHAP) for decoding anxiety-related behaviors [12], [42]. (c) Distinctive Neural Code (DNC) and Linear Discriminant Analysis (LDA) for brain-to-text decoding [20].

lacks scalability and real-time adaptability for dynamically optimizing stimulation parameters.

Neural SoCs enhance precision diagnostics and enable targeted interventions for neurological and psychiatric conditions by leveraging key neuro-markers. For example, a neural synchrony processor facilitates precise phase-locked neurostimulation using SE, PAC, and PLV, supporting interventions for anxiety and OCD [22], [23]. The NeuralTree SoC integrates versatile neuro-markers with ultra-low-power oblique treebased classification and multichannel recording/stimulation, enabling real-time adaptive neurotherapies and advancing implantable neural interfaces [5] (Fig. 3(a)). Alternatively, the SciCNN SoC enables patient-independent epilepsy tracking, eliminating the need for pre-deployment retraining and addressing inter-patient seizure variability [16]. Unlike conventional neuro-marker classifiers, it employs a Seizure-Cluster-Inception CNN on bandpass-filtered EEG/iEEG signals, improving seizure detection in previously unseen patients. However, its computational complexity may pose challenges for low-power implantable applications.

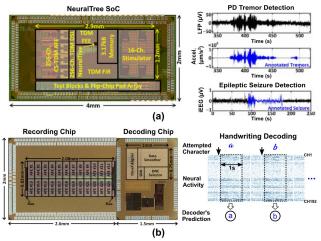


Fig. 3. **Neural SoCs:** (a) Die photo of the closed-loop NeuralTree chip and its experimental results in tremor and seizure detection [5]. (b) Die photo of the miniaturized brain-machine interface (MiBMI) chipset and its decoding results in the handwriting task [21].

# B. Neural SoCs for Prosthetic Applications

Recently, BCIs have shown great potential for restoring lost motor capabilities using powerful yet bulky computing systems; however, there is a growing need for implantable or portable neural prostheses that enable seamless use in daily tasks. These systems typically utilize high-resolution, high-channel-count neural signals recorded from intracortical Utah or high-density ECoG arrays [1], posing scalability challenges that demand computational and hardware efficiency as channel counts increase while maintaining accuracy [46]. Moreover, as neural signals evolve over time due to electrode movement and dynamic brain changes, stable performance requires not only scalable processing but also adaptability via online learning and fast retraining. Consequently, ML SoCs and algorithms must be agile in both training and inference.

Following dense neural recording, these devices extract neural activity features, such as threshold crossings and spiking band power [21], [38] to provide an estimate of neural activity. The neural encoding module then employs ML to capture intricate activity patterns and convert them into actionable commands. So far, only a few studies have explored on-chip decoding for BCI applications due to the challenges of processing high-dimensional data acquired from dense electrodes and the complexity of BCI tasks. An early study developed a neuromorphic SoC for decoding four-class neural activity to control a robotic arm. However, its 16channel recording capacity limited decoding accuracy and task complexity, while also exhibiting low hardware efficiency [47]. Another work used a 128-channel extreme learning machine (ELM) to decode finger movements, implementing the hidden layer on-chip while performing output layer computations on a commercial microcontroller [48]. However, it still relied on an off-chip processing unit to complete the decoding.

A 93-channel intracortical BCI used spiking band power (SBP) features and a steady-state Kalman filter (SSKF) to decode finger movement intentions, but it experienced a latency of up to 2.4 seconds. This system incorporated a commer-

cial Intan analog front-end [38]. Meanwhile, the high-density NeuralTree SoC integrated 256/64-channel ECoG recording and on-chip finger movement decoding using a tree-based neural network. However, it lacked the high-bandwidth spike recording necessary for more complex tasks. These studies highlight the need for advanced ML-integrated BCI chips capable of handling complex tasks such as handwriting.

More recently, the miniaturized Brain-to-Text BCI (MiBMI), integrating a neural recording chip with a decoding chip, was introduced (Fig. 3(b)). It enabled the decoding of intricate motor tasks such as handwriting, using a DNC-based framework combined with LDA. DNCs reduce the dimensionality of neural data and capture complex patterns, enabling fast and accurate letter classification with fewer parameters than conventional models. The measured system achieved a software-comparable accuracy in decoding 31 handwritten letters,  $\sim 3\times$  higher in task complexity compared to state-of-the-art BCI SoCs, with  $> 10\times$  better area and power efficiency, thanks to the use of DNC algorithm and hardware optimizations (e.g., memory sharing). This chipset presents a promising solution for integrating advanced decoding algorithms into compact, low-power BCIs.

## V. CONCLUSION

Integrating neural interfaces with hardware-optimized ML models on SoC platforms enhances efficiency, speed, and accuracy, aligning with the growing demand for real-time neural decoding and closed-loop neuromodulation in assistive devices and therapeutic interventions. By leveraging high-density neural recordings and ML-based feature extraction, these systems enable fast, reliable neuro-marker identification, improving applications such as seizure detection, psychiatric treatments, and motor restoration. The synergy between neural interfaces and ML advances miniaturized, energy-efficient SoCs, paving the way for scalable, self-sufficient, and adaptive neural platforms that drive next-generation BCIs, precision medicine, and intelligent neurostimulation systems.

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