symmetry

MDPI

Review

Energy-Efficient Deep Neural Networks for EEG Signal Noise Reduction in Next-Generation Green Wireless Networks and Industrial IoT Applications

Arun Kumar [1], Sumit Chakravarthy [2] and Aziz Nanthaamornphong [3,*]

[1] Department of Electronics and Communication Engineering, New Horizon College of Engineering, Bengaluru 560103, India; dr.arunk.nhce@newhorizonindia.edu
[2] Department of Electrical Engineering and Computer Engineering, Kennesaw State University, Kennesaw, GA 30144, USA; schakra2@kennesaw.edu
[3] College of Computing, Prince of Songkla University, Phuket 83000, Thailand
* Correspondence: aziz.n@phuket.psu.ac.th

Abstract: Wireless electroencephalography (EEG) has emerged as a critical interface between human cognitive processes and machine learning technologies in the burgeoning field of sensor communications. This paper presents a comprehensive review of advancements in wireless EEG communication and analysis, with an emphasis on their role in next-generation green wireless networks and industrial IoT. The review explores the efficacy of modulation techniques, such as amplitude-shift keying (ASK) and frequency-shift keying (FSK) in EEG data transmission, and emphasizes the transformative role of deep learning in the joint transmission and restoration of EEG signals. In addition, we propose a novel, energy-efficient approach to deep learning-based EEG analytics, designed to enhance wireless information transfer for industrial IoT applications. By applying an autoencoder to sample the EEG data and incorporating a hidden layer to simulate a noisy communication channel, we assessed the energy efficiency and reliability of the transmission. Our results demonstrate that the chosen network topology and parameters significantly affect not only data fidelity but also energy consumption, thus providing valuable insights for the development of sustainable and efficient wireless EEG systems in industrial IoT environments. A key aspect of our study is related to symmetry. Our results demonstrate that the chosen network topology and parameters significantly impact not only data fidelity but also energy fidelity and energy consumption, thus providing valuable insights for the development of sustainable and efficient wireless EEG systems in industrial IoT environments. Furthermore, we realized that the EEG data showed mildly marked symmetry. Neural networks must also exhibit asymmetric behavior for better performance.

Keywords: EEG; deep learning; WBAN; machine to machine; wireless sensor networks

check for updates

Citation: Kumar, A.; Chakravarthy, S.; Nanthaamornphong, A. Energy-Efficient Deep Neural Networks for EEG Signal Noise Reduction in Next-Generation Green Wireless Networks and Industrial IoT Applications. *Symmetry* **2023**, *15*, 2129. https://doi.org/10.3390/sym15122129

Academic Editor: Antonio Palacios

Received: 23 September 2023
Revised: 15 November 2023
Accepted: 23 November 2023
Published: 30 November 2023

1. Introduction

In today's digital age, enhancing quality of life through context-aware solutions and biological monitoring is paramount. As wearable and implantable wireless sensors have become increasingly integrated with next-generation green wireless networks and industrial IoT applications, there is an urgent need for energy-efficient and context-aware solutions. This paper aims to explore how deep neural networks (DNNs) can contribute to this evolving landscape, with a focus on electroencephalography (EEG)-based brain-computer interfaces (BCIs).

BCIs have already demonstrated immense potential for a wide range of applications, from the intuitive control of smart devices and industrial automation to advanced healthcare diagnostics. Unlike other brain-monitoring techniques, such as magnetoencephalography, EEG has emerged as a particularly mobile and non-invasive method that can seamlessly integrate with industrial IoT applications [1].

Wireless body area networks (WBANs) serve as the foundation for these innovations, particularly when connected via machine-to-machine (M2M) connectivity. WBANs have shown their utility in both medical and non-medical domains, including, but not limited to, healthcare, environmental monitoring, industrial applications, entertainment, security, and fitness. This not only reduces the financial burden of in-hospital patient monitoring but also promises a more sustainable approach by leveraging energy-efficient technologies [2].

Within the scope of WBANs, this paper highlights the challenges and opportunities associated with EEG data transmission and processing in next-generation green wireless networks [3]. Given the limited energy resources available for wireless transmission in WBANs, it is imperative to explore efficient methods of EEG data communication. One notable challenge is the potential for increased noise levels during the mobile collection of EEG data [4].

To address these challenges, we propose an innovative approach using deep learning-based autoencoders designed to simulate wireless channel conditions. Our aim is to explore how DNNs can be leveraged to improve the fidelity of EEG signal transmission and significantly reduce the energy consumption and overall data transmission volume. Various architectures and parameters are tested to identify the most energy-efficient and reliable methods for EEG data processing and transmission in industrial IoT scenarios.

In summary, this study shifted the focus from the traditional Fourier domain analysis to a machine-learned feature extraction and reduction approach for EEG signals. This new methodology not only offers significant advancements in feature extraction and noise reduction but also presents a sustainable solution that aligns perfectly with the objectives of next-generation green wireless networks and industrial IoT. Next, we provide the roadmap for the paper to benefit the audience. We begin with a discussion of how EEG is used in modern systems, particularly in machine-to-machine (M2M) communications, wearable IoT systems, and wireless body area networks (WBANs). We detail how aspects such as heterogeneity, energy, and quality of service (QoS) play critical roles. This is followed by detailing the key aspects of signal communications related to wireless EEG, namely power management, MAC and network topologies, and spectrum usage. Next, we survey the research gaps in the current state-of-the-art of EEG signal processing and review recent works that aim to overcome these gaps in Section 3. The gaps consist of how to best collect the data for EEG applications via the channel selection nature of the application. This is followed by a study on the distributed collection and processing of signals captured at separate locations. Finally, Section 4 details how disruptive the technology is: Deep Learning. We demonstrate the novelty we carried out in this regard and compare the work to another existing approach. This is followed by the conclusion section, which summarizes our review and contributions to this paper. We demonstrate that network topology and parameters significantly influence not only data fidelity but also energy consumption, thus providing valuable insights into the development of wireless EEG systems that are sustainable and energy-efficient. Figure 1 shows the structure of the proposed work.

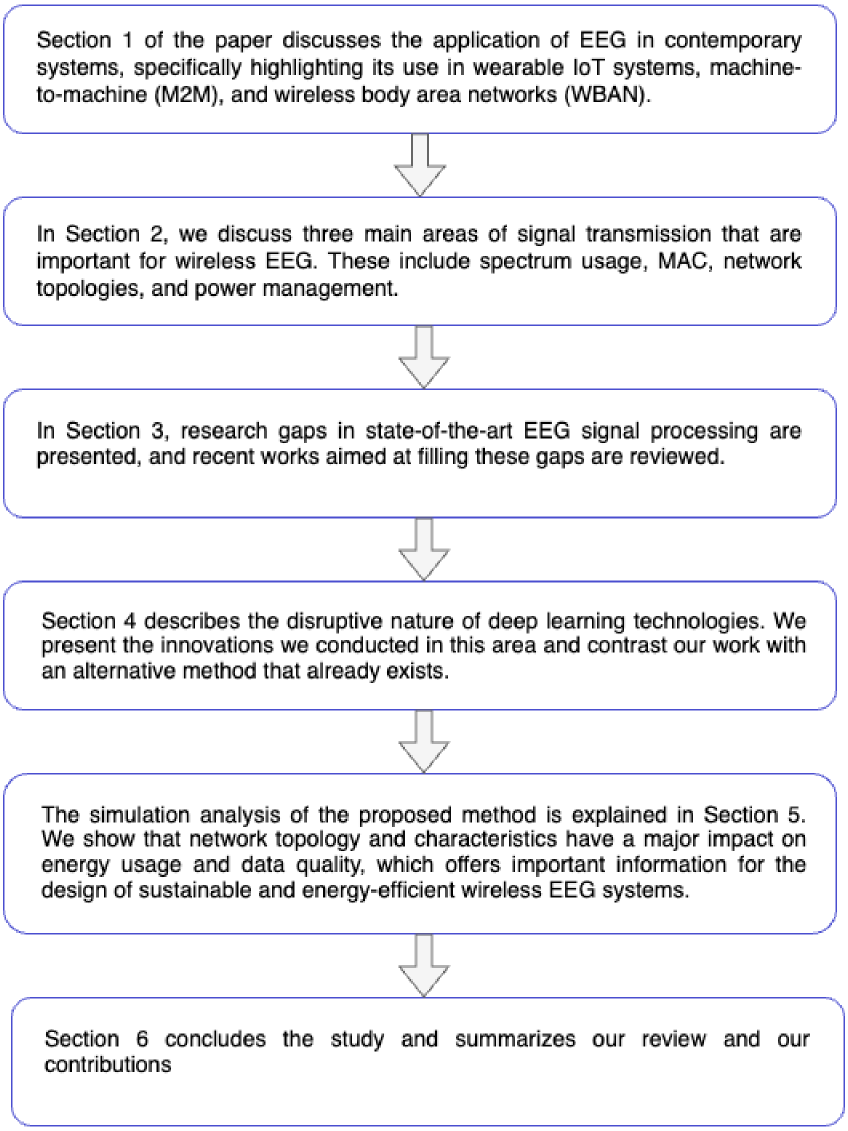

Figure 1. Structure of the proposed work.

2. Current Technologies

In this section, we offer an analysis of essential factors in this field, covering topics such as the latest advancements in EEG technology, machine-to-machine communication protocols, pivotal considerations, and prevailing standards governing brain-machine interface communications.

2.1. EEG in Recent Use

In the past decade, electroencephalography (EEG) has undergone a remarkable transformation, evolving from large, precise, yet cumbersome devices to compact, wirelessly enabled, wearable systems. Traditional EEG setups, characterized by their intricate configurations and time-consuming application procedures, often result in user discomfort [5]. On the other hand, wearable EEG devices, although limited in sensitivity and spectral range owing to cost considerations, offer the advantage of data collection in non-medical settings. This versatility has expanded their application scope to include cognition studies, brain-computer interfaces, educational research, and gaming [6].

Despite its emergent status, the field is primarily propelled by the continuous innovation of new devices that act as crucial links in the development chain. In line with contemporary advancements in WBANs, this study undertakes an exploratory examination of wireless EEG sensor networks, with an emphasis on decentralized signal processing. A wireless encephalography sensor network (WESN) serves as a modular neuromonitoring platform featuring high-density EEG recordings across multiple nodes equipped with electrode arrays, signal processing units, and wireless communication functionalities [7].

We explore the merits of such a modular setup, particularly highlighting how decentralized signal processing algorithms can mitigate power consumption by avoiding centralized data accumulation. One practical application involves a wireless multi-channel EEG system that employs lossless or near-lossless compression algorithms. This creates a low-power platform that is conducive to the development and testing of efficient, low-complexity compression techniques. Publicly accessible EEG databases often act as testing grounds for these algorithms, allowing for comparisons of the compression rates reported in the extant literature.

For instance, consider a 59-channel EEG signal sampled at a rate of 500 Hz and bit depth of 16 bits per sample. These data can be efficiently encoded and transmitted via our proposed platform in the lossless mode, requiring only a current draw of 337A per channel. Importantly, the decompressed signal retains complete fidelity to the original recording, and the experimental section of this paper elaborates on the similar settings employed to generate our results.

Subsequently, we examine core principles of communication technology that enable seamless connectivity in BCI applications. It is worth noting that EEG data are susceptible to various noise interferences such as

- Signal from the heart (ECG, EKG, or electrocardiogram);
- EMG artifacts caused by muscle contractions;
- An electrooculogram (EOG) is a signal produced by eyeball movement;
- Lines of AC power, electronics, etc.

In the context of data processing, employing an encoder-decoder framework effectively mitigates most of these noise components by projecting them into a reduced-dimensional space.

2.2. Digital Modulation for BCI

In the design and development of implantable devices for BCIs, a range of independent metrics, such as spatial distance, information content, dependency, and consistency are employed to assess the suitability of the channel subsets generated through search algorithms. This section emphasizes the significance of achieving high data rates, energy efficiency, and low power consumption in BCIs. We delve into various digital modulation schemes, such as amplitude shift keying (ASK), frequency shift keying (FSK), and phase shift keying (PSK), which are specifically tailored for wireless applications.

A comparative analysis featuring tables summarizing the data rates, CMOS sizes, and other pertinent parameters is presented to highlight the efficacy of these modulation schemes in implantable devices. the thoughtful selection of modulation techniques, coupled with optimized modulator and demodulator designs, can effectively mitigate power consumption and minimize electromagnetic interference with surrounding electronics.

An extensive review of the literature revealed that ASK, FSK, and PSK are commonly employed in wireless implantable devices. Despite these advancements, there are still a myriad of challenges affecting communication systems in contemporary devices. The realm of low-power wireless electronics is a burgeoning field with a significant body of research addressing areas such as biomedical sensing [8], implants [9], wireless sensor networks [8], intelligent biomedical devices [10], and body sensors [11].

A focused analysis of the literature published between 2000 and 2011 revealed developments in low-power transmitters that utilize digital bandpass modulations in implantable devices. For instance, CMOS-based ASK demodulators have been designed to extract and decode digital data from current signals featuring discrete amplitude levels ranging from four to four, with an exceedingly narrow modulation depth of 250 kHz.

In the following sections, we discuss the integration of EEG-inspired technologies into machine-type communication systems, shedding light on both the possibilities and challenges that lie ahead.

2.2.1. M2M Technologies with Application to BCI and EEG

The proliferation of smart interconnected devices has accelerated since the rise of ubiquitous connectivity. Machine-to-machine (M2M) technology is a burgeoning field that facilitates autonomous machine communication and circumvents the need for human involvement. This technology is especially pertinent to mobile health (mHealth) applications, benefiting both healthcare providers and patients. However, M2M presents several challenges and complexities.

As the demand for mHealth solutions continues to escalate, wireless communication remains a central focus, with an emphasis on overcoming the challenges specific to the mHealth and M2M paradigms. Research in this area has recently gained traction, owing to its broad range of applications, benefits, and market potential. Notable works include those by Chi and Cauwenberghs [12], who provide an overview of standardization initiatives and M2M applications, and Nandyala and Kim [13], who explore intriguing network-related challenges.

Additional areas of research include medical sensor design [14–18], body area networks [19,20], and WBANs [21–23]. This paper's unique contribution lies in a comprehensive review of physical layer (PHY) technologies in WBANs, highlighting testbed implementations, and providing an end-to-end overview of M2M systems within mHealth contexts.

EEG is being increasingly employed in BCI systems. Machine learning algorithms applied to EEG data are particularly effective for real-time BCI applications, owing to their capability to learn flexible, nonlinear functions with constant latency. Despite the sensitivity of EEG signals to electromagnetic noise, efforts are ongoing to minimize system jitter and enhance overall reliability.

The Robot Operating System (ROS) offers intriguing parallels to BCI systems; both rely on concurrent communication processes. For example, Beraldo et al. [24] successfully integrated ROS with a BCI for mental control of a telepresence robot. The ROS-Neuro framework capitalizes on the modularity and reliability of ROS, facilitating synergies between bio-systems and robotic systems.

A comprehensive review of the key technological attributes and advancements will follow.

2.2.2. Key Aspects to Consider for M2M and WBAN

This section discusses the pivotal factors to be considered when integrating machine-type applications within wireless brain interface networks. These aspects span traffic types, energy consumption, service quality, system reliability, and user considerations, which are elaborated as follows.

1. **Device and Traffic Heterogeneity:** M2M devices in mHealth often comprise various medical sensors situated on or within the human body. These sensors wirelessly transmit real-time data for continuous patient monitoring by healthcare professionals. Sensors can measure various physiological parameters such as heart rate, muscle activity, and brain signals, whereas actuators act on commands from sensors or manual input to perform specific tasks, such as insulin delivery.
2. **Energy Efficiency:** Given the compact size requirements for body sensors, battery size and life become critical. Replacing batteries, particularly in implantable devices, is highly inconvenient and requires energy-efficient designs. Therefore, low-power transceiver architectures and energy-aware communication protocols are required.
3. **Quality of Service (QoS):** M2M mHealth systems exhibit a broad range of traffic patterns, from low-rate monitoring to high-bandwidth, real-time applications. End-to-end delay is often the most stringent QoS requirement, particularly in real-time

monitoring scenarios. Medical applications typically require support for bit error rates ranging from milli to micro levels with a maximum allowable delay of 125 ms. Alert mechanisms that trigger warnings based on preset thresholds are also integral to the system.

4. **Reliability:** In mHealth applications, reliable data transmission from patients to the medical staff is imperative. WBANs, particularly on the patient's side, are the most vulnerable components of the M2M architecture because of the inherently error-prone nature of biological channels. Consequently, these networks must be designed considering factors such as patient mobility, specific absorption rates (SAR), and the interference environment.
5. **User posture and context:** Although body posture can affect sensor readings, our study assumes that the user is in a sitting position and does not incorporate specific variables in the experiment.

Beyond the previously discussed performance metrics, additional factors such as network topology, transmission protocols, and technology integration must be scrutinized, which are detailed as follows.

1. **Network topology:** In most WBAN setups, star topology is prevalent, where all sensor devices connect directly to a central WBAN coordinator. However, network reliability and energy efficiency can be enhanced by using sensors as relays [25–29]. In M2M communication, point-to-point medium to long-range connections between the gateway and core network are typically assumed (e.g., via WLAN or LTE). Advanced topologies that exploit multiple Wireless Sensor Networks [30] or ambient sensor networks [31] can be considered for efficient routing and cooperation.
2. **Transmission and data retrieval:** mHealth applications necessitate secure wireless transmission and storage of sensitive medical data. Therefore, a robust strategy is imperative to safeguard M2M communications [32]. New schemes must be developed to cater to the unique characteristics of various technologies to create interoperable and technology-agnostic security protocols.
3. **Technology integration:** The wireless technologies employed across different layers of the M2M system have unique challenges and must be meticulously integrated for effective mHealth applications. Access technologies such as LTE, WiMAX, and IEEE 802.11 WLAN must be tailored to meet the specific requirements of WBANs. Customization is crucial for achieving end-to-end quality of service (QoS), scalability, and ubiquitous connectivity. The subsequent section in this chapter will delve deeper into current communication standards, emphasizing the importance of technology integration in machine-type brain interfaces.

2.2.3. Communication Standards for EEG

References discuss recent work on wearable and machine-linked EEG systems and provide current developments in this domain, particularly when they are operated in a wireless environment [33,34].

The IEEE 802.15.6 standard was recently introduced for short-range wireless communications near or within the human body. This standard is particularly suitable for EEG applications for several reasons.

- **Power management:** To extend battery life and comply with safety regulations concerning SAR, IEEE 802.15.6 employs both macroscopic and microscopic power management strategies, including hibernation and sleep modes.
- **Security and privacy:** This standard ensures the timely delivery of alarms in emergency situations and incorporates robust security measures to safeguard patient privacy and data confidentiality.
- **Physical layer technologies:** Three distinct technologies are supported at the PHY layer-ultra-wideband (UWB) PHY, which leverages a wide bandwidth for high perfor-

mance, robustness, low complexity, and ultra-low power; and human body communication (HBC) PHY, which utilizes the human body as a transmission medium.

- **Frequency bands:** The standard accommodates multiple frequency bands, from the unlicensed 2.4 GHz range to the 402–405 MHz Medical Implant Communications Service (MICS) band reserved for medical implants.
- **MAC layer priorities:** IEEE 802.15.6 defines eight user priorities at the MAC layer, where 0 represents the lowest and 7 represents the highest priority, typically used for medical emergencies or implant-related events.
- **Network topology:** WBANs operating under this standard typically use an extended star topology, where all nodes connect directly to a hub or through a single relay node.
- **Access protocols:** Both contention-free and contention-based channels are considered. For the latter, two random access protocols are specified: slotted Aloha and carrier-sense multiple access with collision avoidance (CSMA/CA).
- **Integration with M2M systems:** To enable end-to-end M2M communication, sensors must connect to the Internet via an M2M gateway, typically using WLAN/WMAN standards such as WLAN (802.11), WiMAX (802.16), and LTE/LTE-A.

3. Recent Advanced Methods

Although the previous section offered a comprehensive overview of the underlying technologies employed in machine-type brain interface solutions, the field is in a constant state of evolution. Recent innovations have significantly enriched this domain by introducing novel methods and optimizing existing processes. In this section, we provide an elaborative study of three such advancements in this field, namely, the use of channel selection when utilizing BCI for analysis, the use of compressive sensing to optimize the computational needs of the systems, and finally the use of distributed processing to take advantage of the distributed nature of signal collection and processing.

3.1. Channel Selection for BCI

Channel selection is a critical aspect in the realm of EEG data processing given its role in computational efficiency, overfitting mitigation, and setup time reduction. The principal objectives of channel selection can be summarized as follows: (i) Minimizing the computational complexity by selecting pertinent channels and crucial features, (ii) Curtailing overfitting by excluding superfluous channels; and (iii) Accelerating the setup process. Various algorithms employ signal processing techniques such as time-domain analysis, power spectral estimation, and wavelet transform for feature extraction. Various evaluation methods—filtering, wrapping, embedding, hybrid, and human-were applied to assess the selected channel subset. This subsection aims to categorize and expound on the current advancements in EEG channel selection methodologies.

- **Scalp EEG acquisition:** Typically chosen for its cost-effectiveness, ease of use, portability, and excellent temporal resolution. Two primary modes, bipolar and unipolar, exist for the recording of scalp EEG signals. The International 10–20 system, recommended by the International Federation of Societies for Electroencephalography and Clinical Neurophysiology (IFSECN), guides electrode placement on the scalp.
- **Identification of brain waves:** Frequency bands such as beta, alpha, theta, and gamma encapsulate the most significant data related to human cognitive states. These bands provide invaluable information for diagnosing various mental states and disorders.
- **EEG correlation and extraction:** Channel reduction becomes indispensable when many channels introduce complexity and setup time. Channel reduction is particularly relevant in the development of portable medical systems, where computational efficiency and early seizure detection are crucial [35,36].
- **Developments in EEG-based processing:** Advances in low-cost interfaces have fostered the development of channel selection algorithms. These algorithms target enhancing the model performance, speeding up processing, and enabling dimensionality

reduction. Multiple evaluation methods, such as filtering, wrapping, embedding, and hybrid approaches, have been employed for this purpose.

- **Filtering approach:** Known for its speed and classifier independence, it often requires additional refinement for accuracy [37].
- **Wrapper approach:** Involves using a classification algorithm to evaluate channel subsets, adding an extra layer of scrutiny [38].
- **Embedded approach:** Integrates channel selection and classification, reducing the likelihood of overfitting.
- **Hybrid approach:** A combination of filtering and wrapping techniques was designed to circumvent the need for a stopping criterion [39].
- **Human-guided approach:** This approach utilizes expert judgment in certain applications, such as seizure detection, offering the advantage of reduced computational requirements.

Among the key works in this area are studies on removing channel noise via channel selection, channel selection, and transformation-based signal decoding. According to the reference, (1) noises that are irrelevant to the task should be removed rather than complicated; (2) EEG encodings that are subject-invariant by taking functional connectivity into account. They constructed a task-adaptive graph representation of the brain network based on topological functional connectivity rather than distance-based connections. Additionally, only functional regions relevant to the corresponding intention were selected to exclude non-contributory EEG channels [40].

A brain-decoding model called AdaEEGNet is presented in this study [41]. A reduction in computational costs can be achieved by adaptively controlling the number of input channels, and an improvement in classification accuracy can be achieved by reducing over-fitting. Specifically, a lightweight policy module analyzes which channel is required for decoding current EEG trials.

3.2. Secure Wireless Communications Based on Compressive Sensing

Compressive sensing (CS) has garnered substantial attention across multiple domains, such as wireless communications, image processing, and medical imaging, mainly because of its dual capability of concurrently sampling and encrypting data concurrently. In recent advancements, the secure wireless communications leveraged by CS have necessitated both sparsity and incoherence. To satisfy the sparsity criterion, a signal needs to be sparse or compressible. Concurrently, an incoherence condition mandates a sparse basis and measurement matrix.

Notably, CS significantly outperformed the traditional Shannon–Nyquist sampling theorem in terms of the required sample size for equivalent data recovery. For instance, conventional ECG sampling at 256 samples per second can be drastically reduced in CS, as only the non-zero coefficients in the wavelet or Gabor basis carry pertinent information [42], which translates into a reduced number of required measurements, thereby enhancing the computational efficiency and speed of data recovery.

In the context of BCI and artificial intelligence, five stages delineate the process of identifying specific brain signal patterns.

- **Signal capture:** Brain-measuring hardware captures EEG data, which are subsequently visualized and recorded using SDK or API software.
- **Preprocessing:** This stage entails the removal of electrical interference and musculoskeletal noise to prepare raw signals for further analysis.
- **Feature Extraction:** At this juncture, the most relevant brain patterns are isolated and used as input variables for classifiers [42,43].
- **Classification:** Segregated patterns are classified into discernible categories, serving as a basis for subsequent control interface commands.
- **Control Interface:** Finally, these classified patterns are translated into actionable BCI commands, such as the control of a wheelchair, robotic arm, or drone [44–46].

This subsection underscores the transformative potential of CS in secure wireless communication and BCI, elucidating how its superior sampling capabilities can pave the way for efficient and secure communication channels. In [47], the authors applied the optimized Walsh–Hadamard transform (OWHT) to compress EEG and ECG signals. In addition, local binary patterns (LBPs) are applied to enhance the classification accuracy in signal compression. Using this technique, compressed signals were analyzed for discriminative features. A residual learning algorithm is then used to classify the features. The authors in [48] applied a BCI based on EEG with a customizable configuration for use with cloud architectures to control robotic wheelchairs. Canonical correlation analysis (CCA) and compressive sensing (CS) were applied as novelties, as well as free calibration and a calibration stage for steady-state visual evoked potential (SSVEP)-based BCIs. In TSMC's 65nm CMOS technology, CS-Audio provided the first CS-based compression with a DWT sparsifier on-chip in [49].

3.3. Distributed Signal Processing

This section provides an in-depth investigation of WESNs, specifically focusing on the advancements in distributed signal processing in conjunction with WBANs. Each node within a WESN is equipped with an electrode array, a signal processing unit, and wireless communication capabilities, thereby enabling high-density EEG recordings. We discuss the modular architecture and its benefits, followed by an exploration of how distributed signal-processing algorithms enhance the energy efficiency of WESNs by negating the need for data centralization.

The WBAN comprises various sensing nodes, each integrated with a physiological sensor, a signal processing unit, and wireless communication modules. These networks are often multimodal, allowing the real-time joint analysis of data from different sensor types to improve medical diagnostics. High-density sensing modalities, such as HD-EEG, HD-sEMG, and HD-ECG, are often deployed in mini-scale homogeneous WBANs, which can act as sub-networks within larger heterogeneous WBAN systems. Such systems are particularly useful for long-term neuromonitoring of diseases such as epilepsy, Parkinson's, and Alzheimer's, owing to their low power consumption and potential for miniaturization [50–53].

The most promising technique for long-term neuromonitoring is EEG, owing to its wireless and wearable nature. Despite investments from both academia and industry, current systems still largely depend on bulky headsets and offer limited autonomy. The cost metrics for modern EEG systems are approximately 25 per channel for front-end systems and around 120 for wireless transmission of a single EEG signal [54].

Energy-efficient WESNs have been poised for a paradigm shift using distributed signal-processing algorithms. These algorithms not only reduce the data that each node must transmit but also facilitate short-distance, nearest-neighbor communications, obviating the need for data relays over multiple hops. Previous work has skimmed the advantages of per-channel processing advantages for wireless EEG systems [55,56]. The design of distributed neural network architectures that can perform efficient inference within sensor networks with limited communication bandwidth is shown in [57]. Data are exchanged over bandwidth-limited communication channels between multiple sensor devices to perform a classification task. Starting with a centralized neural network, they transformed it into a distributed architecture where different nodes distribute channels.

Various topologies exist for WESN deployment, each with its merits and drawbacks. Networks with numerous short-range communication links are resilient but may require complex routing owing to their cyclic paths. On the other hand, tree-like topologies are less robust against link failures but facilitate cycle-free distributed signal estimation.

The critical takeaway is that the future of WESNs hinges on the adaptability of distributed signal processing algorithms. By localizing the signal processing, these networks can achieve massive parallelization and low-power operation. Furthermore, these algorithms are entirely scalable, offering a promising avenue for the development of power-efficient long-term neuromonitoring solutions. Case-based electroencephalography (EEG) learning involves presenting real-life examples to enhance the understanding of EEG data interpretation and analysis. These include seizure diagnosis and classification, sleep disorders assessment, epilepsy monitoring unit, neonatal EEG for seizure detection, and drug-induced EEG changes. Using these scenario-based learning tools allows students to gain hands-on experience in interpreting EEG data and making clinical decisions based on real-world situations in educational settings, such as medical schools and neurology residency programs. In our case, we consider populations that are not ridden and have mobility as well as operate in a dynamic and mobile environment or use dynamic equipment.

4. Deep Learning for EEG

In light of recent advancements in machine-brain interface technologies, our research shifts its focus towards a groundbreaking approach utilizing deep learning for both compressed data communication and in-depth data analysis. Specifically, we explore the application of autoencoder techniques for noise reduction in EEG signals. Although autoencoders have previously been employed for noise mitigation in simulated channels, our approach is novel in terms of its integration with EEG data. In this section, we detail our innovative methodology and follow it with experimental evidence demonstrating the efficacy of deep learning in both the compression and analysis of EEG signals.

4.1. Deep Learning and EEG

In this subsection, we discuss how deep autoencoders (AEs) are employed to dimensionally reduce raw EEG channels in real time, thereby yielding a more streamlined and cleaner signal. Our study elaborates on how these AE-based deep learning models can be effectively applied to BCIs. In subsequent experimental discussions, we obtained quantitative results demonstrating the efficacy of our model for signal compression. This compressed signal allows efficient downstream processing with a negligible time lag.

A considerable amount of existing research aims to enhance traditional machine learning classifiers by incorporating various pre-trained AEs. Pioneering work in this area, such as that by Hassani et al. [56], integrated machine learning with BCI systems using deep belief networks and denoising AEs. This paper also covers the complexity of classifying motor imagery data, especially when tainted by artifacts, through classifiers that combine Lomb-Scargle periodograms with denoising AEs and Support Vector Machines (SVMs).

A major challenge facing BCI systems is the variability in their performance across different subjects. Various techniques have been explored to enforce subject-invariant feature representations. Yao et al. [58] approximately 75% accuracy in multi-subject motor imagery classification by employing AEs in feature learning and gradient-boosted decision trees in classification tasks. Furthermore, deep learning has shown promising results in recognizing P300 components, even outperforming standard machine learning classifiers through the use of sparse AEs.

Advancements in computing capabilities have enabled the development of large and complex models. For example, attention-based neural networks have been applied to classify briefly heard musical snippets with approximately 37% accuracy [59]. Moreover, adversarial networks have been deployed to induce domain-invariant feature representations, leading to accuracies greater than 60% [60]. Studies have also explored the categorization of motor imagery activities using more intricate models that combine motor execution and motor imagery EEG data [61,62].

Convolutional neural network (CNN) autoencoders serve as efficient tools for capturing the spatial and structural characteristics of data. Generally, they are composed of two main types of layers:

- Convolutional layers: Specialized in feature extraction.
- Pooling layers: Focused on reducing the dimensionality of the data.

This architecture allows CNN autoencoders to perform various tasks related to EEG signal analysis.

A convolutional layer employs filters, k_{ij}^{l}, which are generally much smaller than the dimensions of the input data and constitute a locally connected structure. Each filter in layer l generates feature maps X_j^l by convolving with input $X_i^{l=1}$ and adding biases b_j^l. Subsequently, these features undergo a nonlinear transformation $f(\cdot)$, formulated as:

$$X_j^l = f\left(\sum_{i=1}^{M^{(l-1)}} X_i^{(l-1)} * k_{ij}^l + b_j^l\right)$$

Here, $M^{(l-1)}$ signifies the number of feature maps in the preceding layer $l-1$, and $*$ represents the convolution operation.

The pooling layer considers the roles of the feature selection and data filtration. Both max and average pooling are frequently employed pooling operations. Max pooling selects the maximum value within a given sub-region, whereas average pooling calculates the mean value. Typically, a fully connected layer precedes the output layer, which is often a softmax layer, thereby transforming the features into a long 1D vector.

4.2. EEG Signal Compression with Deep Convolutional Autoencoders Integrated into Real-Time BCIs

EEG-based BCI applications require the computation of intricate functions over noisy EEG channels. In online BCI settings, deep learning algorithms have the advantage of constant processing latency, allowing them to learn nonlinear functions directly from the data. Minimizing system jitter is crucial to avoid unpredictable behavior. We introduce a novel encoding algorithm based on deep convolutional autoencoders, integrated into a ROS-Neuro node. This enables seamless integration of ROS-based BCI and robotic systems for practical applications. The experimental results confirm that our system can generate compressed yet informative encodings from raw input data.

Deep learning (DL) algorithms have proven to be effective for processing physiological data, making them an ideal fit for the ROS-Neuro framework. We introduce a ROS-Neuro node capable of efficiently encoding EEG-based BCI signals in real time using DL models. Raw EEG channels undergo real-time dimensional reduction via a deep autoencoder (AE), leading to a cleaner and more compact input representation.

First, we detail the AE model employed before discussing its practical deployment. Quantitative results for signal compression tasks illustrate the model's efficacy in generating an efficient, easily manipulable representation of the raw input with minimal time jitter.

Earlier research primarily aimed to enhance the accuracy of traditional, non-deep classifiers using various unsupervised trained AEs. Spatially, many matrix elements in the input are zeroed out, offering no information to the downstream processes. Moreover, much of the input is redundant because of the high correlation between the remaining channels. Given that the most meaningful EEG information arises from the slow temporal evolution of channels rather than localized nuances, high-frequency sampling is generally not required. To retain the essential information of the input while potentially discarding noise, it is advantageous to encode a segment of the input into a compact representation. The AE comprises two sub-models: a decoder $x = g(z)$ and an encoder $x = f(x)$, trained using gradient descent to minimize the loss function $L_{AE} = \|x - g(f(x))\|$. The resulting latent code z serves as a compressed representation of x.

For the AE, the input was passed through convolutional layers with ReLU activation, followed by batch normalization layers. Max-pooling is applied post-convolution to improve the spatiotemporal invariance of the representation. The output was then flattened into a 1D vector and passed through a layer of 128 neurons to generate the final code. In the decoder, 3D deconvolutions replace convolutions to reverse the effects of max-pooling. This design enables faster computation by downstream nodes, making the model well-suited for real-time data-processing tasks. Regarding the hyperparameters, an empirically optimized network architecture was adopted, and 5-fold cross-validation was performed to select the optimal model.

4.3. Current Works in EEG Deep Learning

In this subsection, we review the current key works that utilize deep learning in a wireless wearable EEG setting.

In [63], using a single-channel EEG, a lightweight deep learning (DL) model for classifying sleep stages was presented. It was designed to operate on energy- and memory-constrained devices for real-time processing at the edge. Four convolutional filters reduce the data to manageable dimensions, and time-variant features are extracted using transformers. A publicly available dataset (sleep-EDF) was used to train and test the model. In [64], behind-the-ear (BTE) EEG together with TinyML was used to measure the driver's drowsiness in an alight wireless manner. However, such a system may not be able to capture all variations occurring in scalp EEG and is only limited to detecting eye movements. Using anisotropic diffusion properties in electrical circuits and a neural network architecture, Ref. [65] introduced a novel all-analog convolutional processing unit (CvPU). Compared with current digital architectures and hybrid analog-digital approaches, the proposed architecture consumes one to three orders of magnitude less power. Although it is a novel approach for neural processing, the hardware size has increased significantly which makes such systems incompatible for wearables. According to [66] a BCI interface identifies and controls seven wheelchair movements: forward, backward, left, right, up, and downstairs. Filtered raw signal data were collected by electroencephalography (EEG) from healthy volunteers and then classified using deep and shallow learning. Such noise removal may not be efficient and may result in data loss. Three classification algorithms were used to evaluate our approach: CNN (CNN), support vector machines (SVMs), and random forest classifiers in [67], which used a convolutional neural network (CNN) and bidirectional long short-term memory (BLSTM) model on collected EEG data to understand whether students were confused. In such cases, the novel but heavy workload of machine learning makes its use in wearable devices challenging.

5. Experiments

A specialized command for training autoencoders exists within MATLAB's deep learning toolbox. Although it is straightforward to simply employ input data as a cell array, this method proved incompatible with the project early on. The issue lies in the nature of the output, which is formatted as an object file. While most networks in MATLAB's version 2016. toolbox are constructed as Directed Acyclic Graphs (DAG), which can be easily modified, the output from the autoencoder command is an unmodifiable object. Given the need for customizable architecture, this built-in option is not viable.

The drive behind developing a network that can auto-encode EEG signals lies in achieving signal compression that is resilient to noise. All subsequent networks were developed with this objective. Identifying the patterns in EEG signals for effective compression remains a challenging task.

5.1. Prototype Network One

The initial network served as a proof-of-concept and did not incorporate any noise input. It successfully encoded the EEG signals with a root mean square error (RMSE) output of one. Once this preliminary stage was completed, the second network was designed, the architecture of which is shown in Figure 2. This network features two fully connected layers equipped with ReLU (rectified linear unit) activation functions on the encoder side, whereas the decoder side consists of a single fully connected layer.

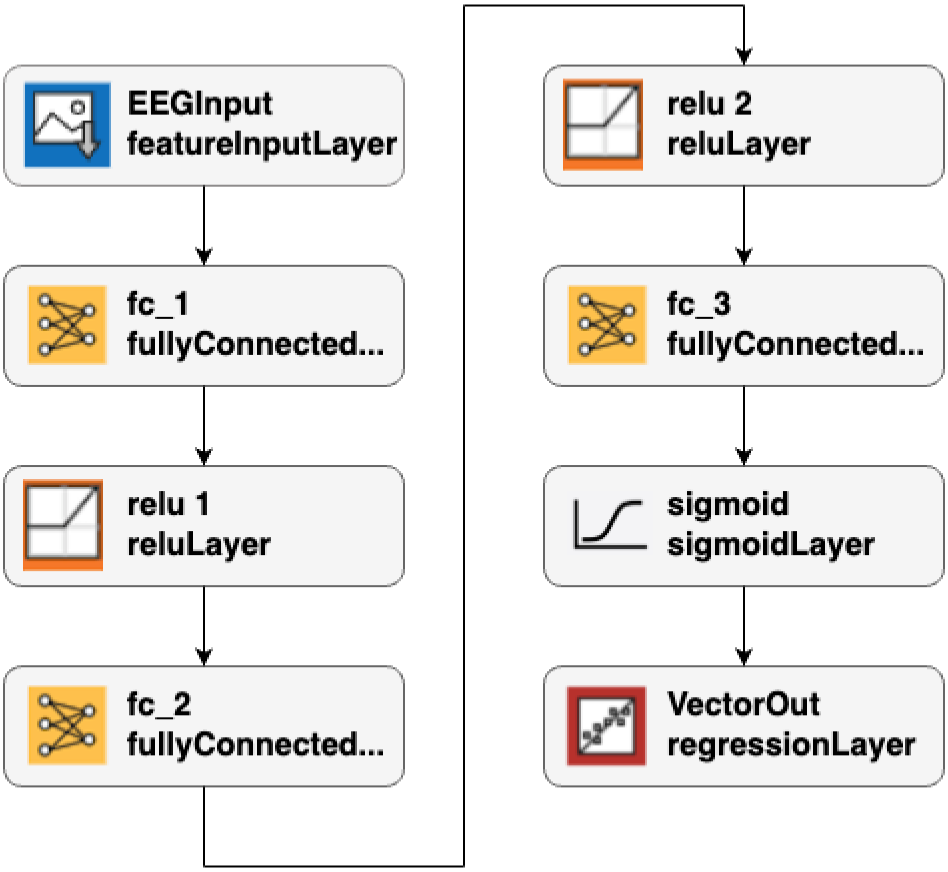

Figure 2. Prototype one architecture.

It is noteworthy that the majority of the outputs tended to be zero when testing only the encoding portion of the autoencoder with the input data. This can be attributed to the ReLU layer, which filters out the negative values. Intriguingly, these zeroed nodes remained consistent across the various training examples, suggesting that the network did not utilize them. This leads to two conclusions: the network has built-in redundancy, even without noise, and the hidden layer size can likely be reduced because not all nodes are active. If these zero neurons were to toggle randomly, it could mimic the effect of a dropout layer. In any case, the presence of these inactive nodes reduces the likelihood that added noise will corrupt significant data, thereby enhancing the redundancy of the encoding, which is a promising development for the experiment.

As for data formatting, using raw EEG data as input led to scaling issues, often resulting in NaN values. This is primarily because when a large-scale input passes through a sigmoid layer, it is almost inevitably converted to either one or zero. To address this, we normalized the signal by subtracting its lowest value and then dividing it by its highest value. This process effectively scales the signal to a range between zero and one without losing any information. The signal retains its original shape, and all values remain proportional to each other. The transformation is linear, involving only additive and multiplicative operations, which allows for easy processing by the autoencoder and straightforward reversal, as long as the maximum and minimum values are preserved.

5.2. Prototype Network Two

The second network introduces a noise channel by incorporating a second input filled entirely with random noise. This noise input is combined with the hidden layer via an additional layer. During training, the network rapidly adapted to this configuration and effectively compensated for introduced noise. The architecture of the second prototype network is illustrated in Figure 3.

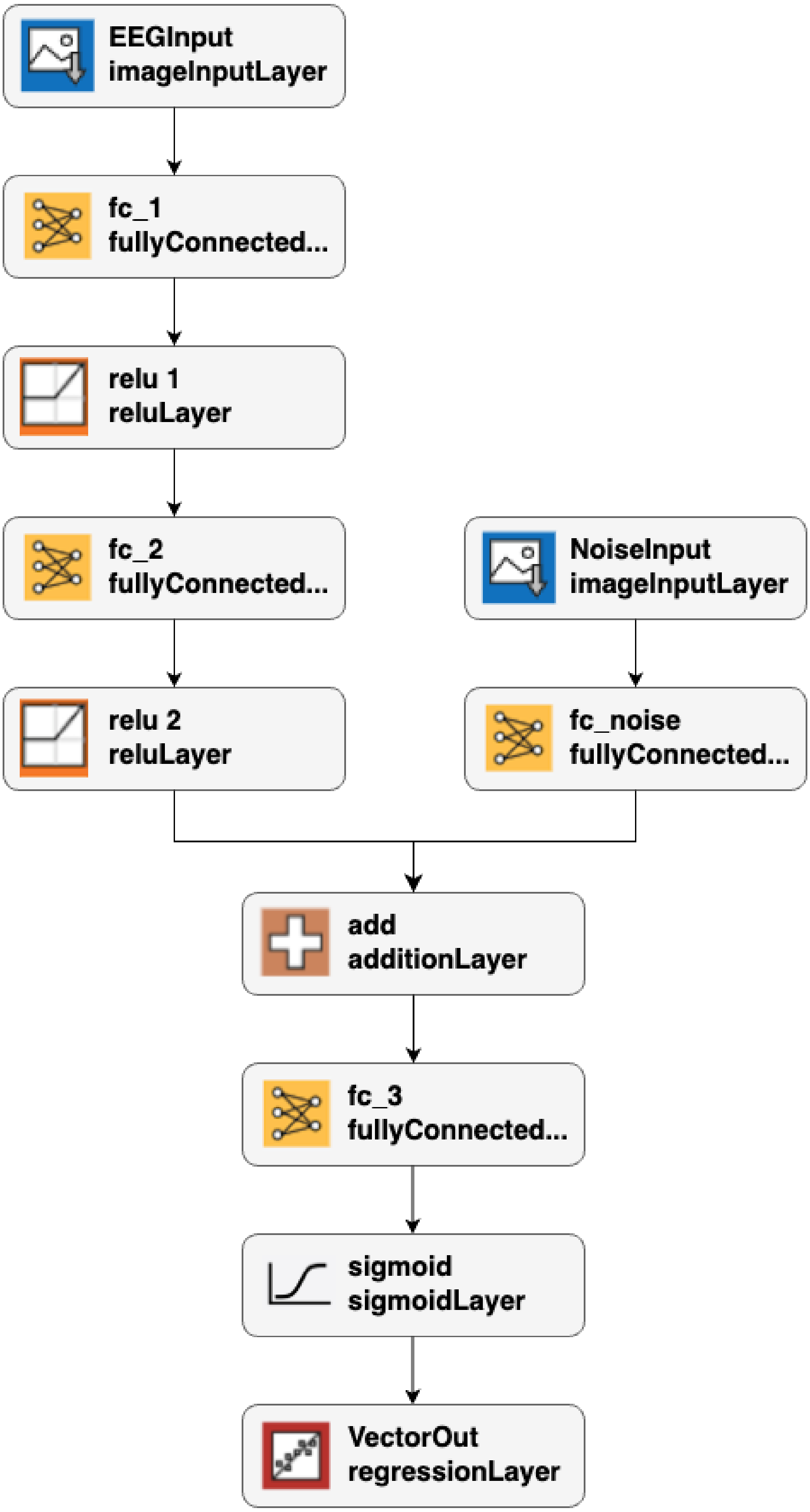

Figure 3. Prototype two architecture.

Upon completing the training for both networks, a program separates the autoencoder into distinct encoder and decoder components. This allowed for the independent study of each section. Although it is possible to input data into either the encoder or decoder for analysis, obtaining meaningful output from the decoder using random input data is challenging. This is due to the fact that the encoder and decoder were co-developed; although the decoder can produce weakly accurate outputs, truly meaningful results require input data that has passed through the encoder. Figures 4 and 5 present the architectures of the encoder and decoder sides, respectively, where the EEG channels are treated as image data for the network input.

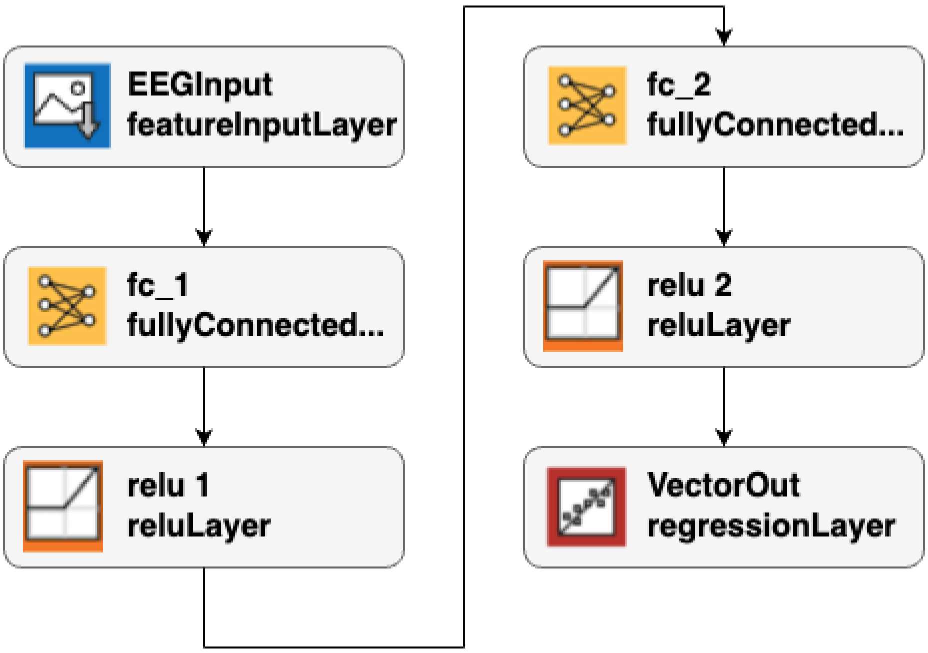

Figure 4. Prototype two encoder architecture.

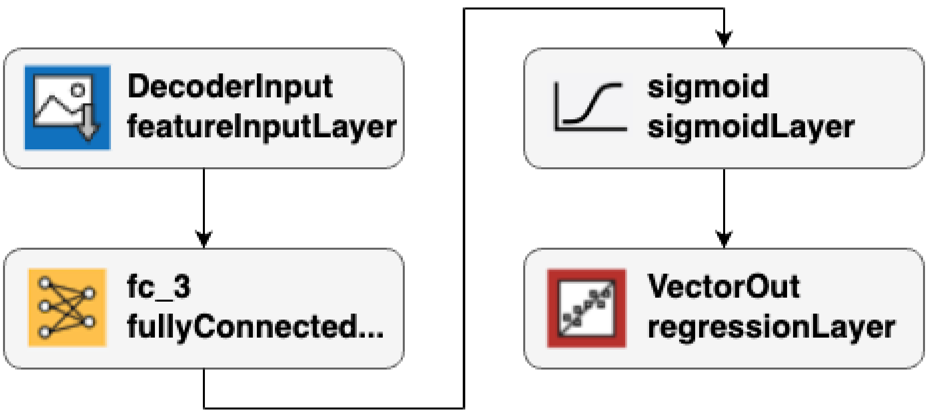

Figure 5. Prototype two decoder architecture.

5.3. Noise Simulation Network

The third network introduced a helper layer as a substitute for directly adding noise to the central layer of the network. There were several reasons for this adjustment. Initially, noise was added to the center layer to mimic the behavior of digitally modulated channels. However, the previous method of simulating additive noise did not accurately reflect the nature of noise in digital systems. In these prior experiments, both the channels and added noise behaved as if they were part of an analog system. In this scenario, the noise slightly distorts the original signal, which can still be separated. However, in digital systems, the added noise can flip the bits in a channel, resulting in a nonlinear effect that cannot be easily simulated by simply adding noise. This is where the specialized helper AEW layer proves to be useful.

Another advantage of the helper AEW layer is its ability to emulate the characteristics of a digital channel. The layer comes with editable parameters, such as NoiseMethod, EbNo, SNR, BitsPerSymbol, and SignalPower, all of which contribute to a more accurate simulation of a noisy digital environment. Figure 6 depicts the architecture of the network. It is worth noting that calculating the area under the curve, taking its square root, and dividing by the length yields the RMSE.

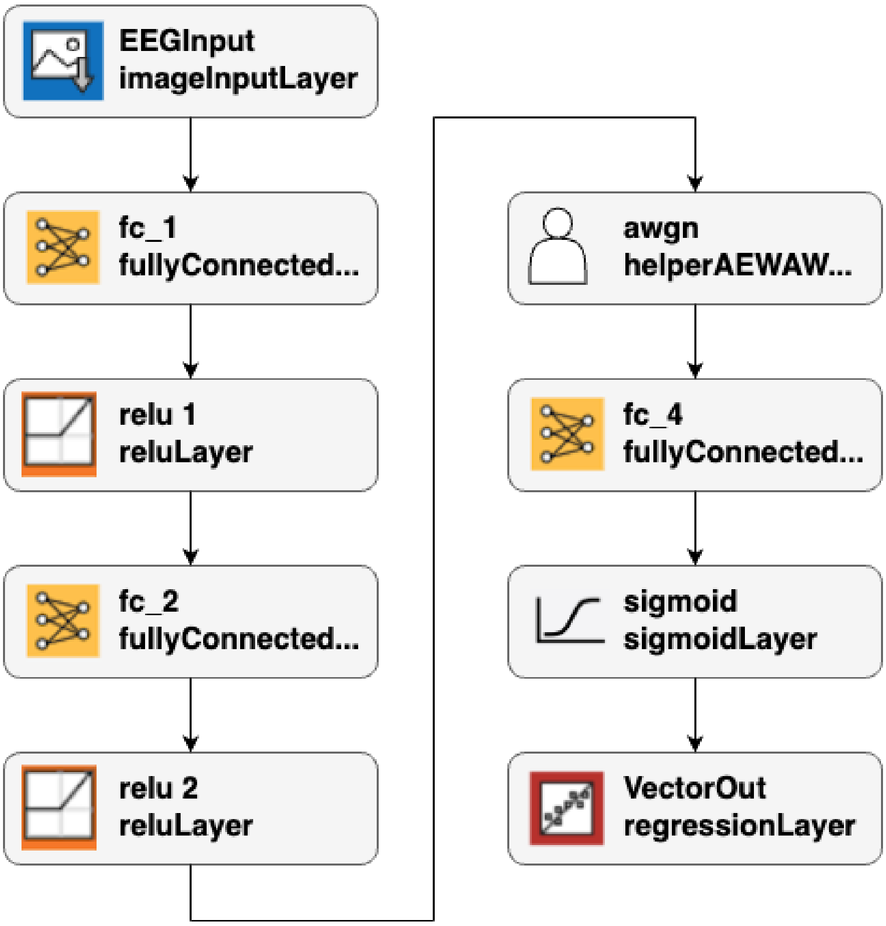

Figure 6. Noise simulation network architecture.

An important consideration for the third network is that high precision may not be necessary, and rounding the values to the nearest digit may be beneficial. Digitizing the input in this manner simplifies the training process for the autoencoder. This concept forms the basis for subsequent network configurations. Because this setup is essentially the same design but with a different data format, it is not categorized as a fourth network but rather as a variation of the third.

5.4. Network Results

A notable issue with the original network is its relative "weakness", which means that subsequent versions outperformed it by a significant margin. It also produced "fuzzy" outputs at certain points; it seemed to align well with the input initially, but then started to oscillate, failing to closely match the input. Given that these autoencoders are generated using a standard command rather than a custom-designed architecture, options for improvement are limited, necessitating the development of a new network.

The first network served primarily as a proof of concept and an introduction to how MATLAB autoencoders functioned. Its performance was reasonably good, maintaining a low output cost. The hidden layer may even be further reducible, considering the presence of redundant zeros.

In contrast, Network 2 achieved a similar RMSE to Network 1 by the end of training, even with added noise interference. This is encouraging, but it appears that the RMSE does not drop below 1, regardless of the training duration. Several factors could account for this plateau, such as inherent noise in the sample data or diminishing gradients towards the end of the training process.

5.5. Troubleshooting

This section provides an overview of the problem-solving steps undertaken to bring a network to a functional state.

5.5.1. Variations in Experiment

The experiments were conducted under two distinct categories. The first involves altering the network architecture and its parameters. This includes modifications to the architecture's topology, adjustments to the ReLUs, and variations in the operating conditions of the network. Each architectural modification aimed to assess the effectiveness of different structural configurations. Tweaks to ReLUs focus on examining how changes in a network's nonlinear components affect its performance. Altering parameters aimed to study how the network responds under various wireless channel conditions.

The second category pertains to manipulations of the input or output data prior to training. Two sub-categories within this are moving averages and reduced sample sizes. The moving average experiments seek to determine if noise can be filtered out while minimally affecting the input data, thereby improving network performance. The reduced sample size experiments aimed to gauge the network's efficiency when it was trained on smaller sets of input data. Table 1 provides a comprehensive summary of the performance metrics for the various architectural and experimental variations measured in terms of the root mean square error for mini-batches. Additionally, the table incorporates testing data, albeit not to scale drawn from four test runs based on the original dataset to facilitate comparative analysis.

Table 1. Experiment variant results.

	Default	**Architecture 2**	**Architecture 3**	**Architecture 4**
Training Loss after 200 epochs (Mini Batch RMSE)	3.65	2.33	2.29	3.61
(Mini Batch MSE)	13.3225	5.4289	5.2441	13.0321
Testing RMSE	0.639	0.6529	0.427	0.3744
Testing MSE	0.408	0.426	0.182	0.14
	Different ReLUs	Moving Average	Changed Parameters	Smaller Sample Size
Training Loss after 200 epochs (Mini Batch RMSE)	3.65	3.72	3.67	3.52
(Mini Batch MSE)	13.32	13.83	13.46	12.39
Testing RMSE (Four test samples)	0.6365	0.632	0.6378	0.6458
Testing MSE	0.405	0.399	0.406	0.417

In the majority of the experiments, the RMSE for the test data remained consistent, indicating that overfitting is not an issue in these tests.

5.5.2. Change in Architecture

Various architectural changes were tested to evaluate this system. In both experiments, additional layers were incorporated into the network, increasing the training time and enhancing the overall performance. The second architecture expands the size of the existing layers, featuring 10,000 neurons in the first encoding layer instead of the default 2500 and 5000 neurons in the hidden layer as opposed to 1000, and maintains the final layer size at 13,500. Although this resulted in a reduced final RMSE of approximately 2.33, the test data did not show similar improvements, suggesting the onset of overfitting. Simply increasing network size does not necessarily yield an effective model.

The third architecture modifies the default setup by maintaining the layer sizes, but adding another layer of equal size to the hidden layer, directly following the channel layer. This change specifically aimed to augment the decoder's capabilities, substantially improving the overall performance of the network. The training results were comparable to those of the second architecture, but with superior testing scores and fewer neurons, demonstrating the advantage of a "deep" network over a "wide" network.

Architecture 4 evolves from the third model by adding a connected layer and ReLU layer before the hidden layer, while also reducing the size of the hidden layer to 2500. This setup was designed to explore the ability of the network to manage further bottle-necking before the channel layer. The results were mixed: the training data remained relatively constant, but the testing data showed improvement. Given more training iterations and data, this architecture may present a viable alternative to the existing models.

5.5.3. Smaller Channel Sample

In this experiment, the input data consisted of 27 channels, of which a select number was used. Specifically, ten channels were chosen for the test. A random permutation dictates the channels selected for the input. Using fewer channels allows us to test the network's performance with scaled-down inputs while maintaining their relational structure. The resulting output was found to be on par with the original architecture. It should be noted that the displayed figures feature a different dataset as the datasets were randomly selected for this experiment.

5.5.4. Leaky ReLUs

In all of these experiments, ReLUs were employed following the fully connected layer to introduce nonlinearity to the function. Without ReLUs, the network performs a series of sequential matrix operations. A standard ReLU allows only positive input values to pass through, setting all other values to zero. A leaky ReLU, however, differs in that it permits a minor fraction of negative values to "leak" through, scaled down by a predefined factor. In this experiment, the scaling factor was set to 0.05.

5.5.5. Moving Average

A challenge specific to EEG data is the difficulty of distinguishing noise from actual electrical signals. Although these networks are designed to address this issue, preprocessing the data can still make them more manageable for the network. In this experiment, a moving average operation was applied to the input data. This allows for clearer retention of the signal in contrast to the noise. However, this approach presents its own set of challenges. For instance, it effectively incorporates future values into the earlier parts of the function, meaning that some segments of the function may contain information about future events without a clear understanding of the inherent structure. Additionally, the performance metrics indicate that this method slightly underperforms compared with the default setup. One possible explanation for this could be the dampening of high frequencies during the moving average process, which may result in the loss of crucial information.

5.5.6. Changed Noise Characteristics

The last variation focuses on altering the characteristics of the noise channel, known as the helperAEWAWGN, which mimics a radio channel using various parameters. The parameters relevant to our study include EsNo (error ratio), SNR (signal-to-noise ratio), BitsPerChannel, and SignalPower. Adjusting these parameters allowed us to simulate the varying levels of noise. For this experiment, we updated the default settings to new values, as detailed in Table 2. In both scenarios, the noise method employed was EsNo.

Table 2. Parameters.

	EbNo	EsNo	SNR	BitsPerSymbol	SignalPower
Default Parameters	10	10	10	1	1
New Parameters	20	20	20	2	1

5.6. Advantages of the Use of Deep Learning Approach

Through the use of deep learning, sensor communication systems can be enhanced to more accurately interpret and act on brain signals. This advancement paves the way for the development of more sophisticated sensory substitution systems. By examining EEG signals, researchers can rapidly develop a comprehensive understanding of brain sensory processing. Overall, deep learning in the context of EEG holds the promise of transforming sensor communications, facilitating the creation of advanced brain-computer interfaces and state-of-the-art sensory substitution systems.

5.7. Complexity

The following formula generates the model computational complexity: $|w| + |dw| + (n+1)kp$ bytes, where w and its gradient size correspond to the number of elements in the weight matrix, number of neurons, and bias connections. We see from the complexity analysis that our deep learning complexity is adjustable and malleable to accommodate system resources and, thus, is not a limitation for wearable devices.

5.8. Study of Symmetry

The study of EEG data shows that it is mild to markedly asymmetric in nature. This implies that neural networks are efficient enough to capture and understand asymmetry. The following aspects were considered to ensure the performance of the neural network: An asymmetric network results if it is initiated at a constant weight. The bias can be kept constant while the weight is randomly initialized. Even with this, more is needed because too small a weight leads to vanishing gradients, whereas too large a weight leads to exploding gradients. Set a specific range for the weight. Table 3 presents comparative results.

Table 3. Comparison with relevant works.

Parameters	[63]	[64]	[65]	[66]	[67]	Our Work
Lightweight algorithm	✓	✓	✗	✗	✗	✓
Multiple channel data	✓	✗	✗	✓	✓	✓
Location Invariant data capture	✗	✗	✓	✓	✓	✓
Lossless data reduction	✗	✗	✗	✗	✗	✓
Novel deep learning	✗	✗	✓	✓	✓	✓
Hardware complexity	✓	✗	✗	✗	✗	✓

6. Discussion and Conclusions

Although numerous studies have explored the application of deep learning to EEG signal analysis, our work introduces a novel approach: the incorporation of noise into the hidden layer of autoencoders. This enhancement substantially broadens the potential of applications involving multiple small sensors that transmit data concurrently. The flexibility of our approach opens avenues for further optimization and expansion in future research.

Our study has not only focused on the introduction of integrated management across energy hubs but has also provided a thorough evaluation of the transition towards smart energy systems. However, it is important to note the limitations of the current network, particularly its ineffectiveness as a compression method compared to a baseline EEG signal. This suggests that while the network has room for improvement, increasing its size or depth could make it applicable in practical settings. Among the variables affecting network performance, the architecture of the network appears to be the most critical, outweighing other factors such as preset parameters and data preprocessing techniques.

Our experiments have shown that various adaptations of the autoencoder network yield similar performances, with the most significant performance boost stemming from adding extra layers rather than increasing the number of neurons in the existing layers. Moreover, the network seems to perform optimally around the central part of the EEG signal, facing challenges towards the end of the signal. Future studies should consider conducting experiments with a deeper network architecture as a new standard to examine its efficacy.

Although we have demonstrated significant improvements in the processing and transmission of EEG signals using machine learning, several challenges remain. These include refining data collection methods, simplifying the complexities inherent in machine learning algorithms, and addressing ethical and privacy concerns related to the application of machine learning in healthcare settings. Future developments and advancements in wireless EEG (Electroencephalography) are anticipated. For the wireless EEG landscape, several trends and possibilities emerge as technology evolves: miniaturization and wearability, improved signal quality, increased mobility and accessibility, IoT integration, cloud computing and big data analytics, advanced signal processing and machine learning, closed-loop neurofeedback systems, and ethical and privacy considerations. Wireless EEG technology will have a profound impact on neuroscience research, clinical diagnostics, and everyday applications. Innovative solutions to brain function and neurological disorders are likely to emerge as these devices become more accessible.

Author Contributions: Conceptualization, formal analysis, writing–original draft preparation A.K.; methodology, S.C.; validation, writing—review and editing, A.N. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by College of Computing, Prince of Songkla University, Thailand.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Famoriji, O.J.; Ogundepo, O.Y.; Qi, X. An intelligent deep learning-based direction-of-arrival estimation scheme using spherical antenna array with unknown mutual coupling. *IEEE Access* **2020**, *8*, 179259–179271. [CrossRef]
2. Famoriji, O.J.; Shongwe, T. Electromagnetic machine learning for estimation and mitigation of mutual coupling in strongly coupled arrays. *ICT Express* **2021**, *9*, 8–15. [CrossRef]
3. Thakur, N.; Han, C.Y. An intelligent ubiquitous activity aware framework for smart home. In Proceedings of the Human Interaction, Emerging Technologies and Future Applications III: Proceedings of the 3rd International Conference on Human Interaction and Emerging Technologies: Future Applications (IHIET 2020), Paris, France, 27–29 August 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 296–302.
4. Mekruksavanich, S.; Jitpattanakul, A. Smartwatch-based human activity recognition using hybrid lstm network. In Proceedings of the 2020 IEEE Sensors, Rotterdam, The Netherlands, 25–28 October 2020.

5. Al-Kadi, M.I.; Reaz, M.B.I.; Ali, M.A.M. Evolution of electroencephalogram signal analysis techniques during anesthesia. *Sensors* **2013**, *13*, 6605–6635. [CrossRef]
6. Bera, T.K. A Review on The Medical Applications of Electroencephalography (EEG). In Proceedings of the 2021 Seventh International Conference on Bio Signals, Images, and Instrumentation (ICBSII), Chennai, India, 25–27 March 2021; pp. 1–6.
7. Jamil, N.; Belkacem, A.N.; Ouhbi, S.; Lakas, A. Noninvasive electroencephalography equipment for assistive, adaptive, and rehabilitative brain–computer interfaces: A systematic literature review. *Sensors* **2021**, *21*, 4754. [CrossRef]
8. Baqai, A.; Umrani, F.A.; Chowdhry, B.S. Led based optical wireless communication system for WBAN. *Mehran Univ. Res. J. Eng. Technol.* **2016**, *35*, 667–672. [CrossRef]
9. Teshome, A.K.; Kibret, B.; Lai, D.T. A review of implant communication technology in WBAN: Progress and challenges. *IEEE Rev. Biomed. Eng.* **2018**, *12*, 88–99. [CrossRef] [PubMed]
10. Mercuri, M.; Karsmakers, P.; Vanrumste, B.; Leroux, P.; Schreurs, D. Biomedical wireless radar sensor network for indoor emergency situations detection and vital signs monitoring. In Proceedings of the 2016 IEEE Topical Conference on Biomedical Wireless Technologies, Networks, and Sensing Systems (BioWireleSS), Austin, TX, USA, 24–27 January 2016; pp. 32–35.
11. Arbi, K.F.; Kromba, I.; Saffih, F.; Amina, B.R.; Slami, A.; Hadjersi, A.; Soulimane, S.; Nigassa, M.E.B. Intelligent IoT (I 2 oT) Biomedical Wearable System based on Smartphone Application. In Proceedings of the 2020 IEEE 5th Middle East and Africa Conference on Biomedical Engineering (MECBME), Amman, Jordan, 27–29 October 2020; pp. 1–4.
12. Chi, Y.M.; Cauwenberghs, G. Wireless non-contact EEG/ECG electrodes for body sensor networks. In Proceedings of the 2010 International Conference on Body Sensor Networks, Singapore, 7–9 June 2010; pp. 297–301.
13. Nandyala, C.S.; Kim, H.K. From cloud to fog and IoT-based real-time U-healthcare monitoring for smart homes and hospitals. *Int. J. Smart Home* **2016**, *10*, 187–196. [CrossRef]
14. Pigeon, M.; Buckley, J.; Barton, J. Wireless Implantable Medical Device: In-body EM losses for a multilayer body model. In Proceedings of the 2021 IEEE Asia-Pacific Microwave Conference (APMC), Brisbane, Australia, 28 November–1 December 2021; pp. 389–391.
15. Li, K.; Zhuang, S.; Liu, J.; Guo, A.; Wang, A.; Lu, J.; Xue, F. Design of an intelligent medical splint with 3D printing and pressure detection. In Proceedings of the 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Nanchang, China, 26–28 March 2021; pp. 655–658.
16. Tuan, C.C.; Lu, C.H.; Wu, Y.C.; Yeh, W.L.; Chen, M.C.; Lee, T.F.; Chen, Y.J.; Kao, H.K. Development of a system for real-time monitoring of pressure, temperature, and humidity in casts. *Sensors* **2019**, *19*, 2417. [CrossRef]
17. Maag, A.-L.D.; Laufer, S.; Kwan, C.; Cohen, E.R.; Lenhart, R.L.; Stork, N.C.; Halanski, M.A.; Pugh, C.M. Sensor-based assessment of cast placement and removal. *Stud. Health Technol. Inform.* **2014**, *196*, 259.
18. Wang, J.; Guo, Y.; Li, G.L. Current status of standardization of traditional Chinese medicine in China. *Evid.-Based Complement. Altern. Med.* **2016**, *2016*, 9123103. [CrossRef] [PubMed]
19. Alqahtani, M. IOT within the Saudi Healthcare Industry during COVID-19. In Proceedings of the International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2021 (Volume 1), Al Buraimi, Oman, 25–26 June 2021; Springer: Berlin/Heidelberg, Germany, 2022; pp. 469–483.
20. Cheng, L.; Hao, C.; Li, H.; Chi, Z.; Guo, L.; Wu, Y.; Chen, S.; Hu, H.; Liu, X.; Bai, X.; et al. The Application of Sensors in the Auxiliary Medical Devices. In Proceedings of the 2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Shanghai, China, 23–25 October 2021; pp. 1–5.
21. Kong, L.; Cheng, L.; Wan, P.; Liu, X. Development and Intellectualization of Ramie Fiber Composites Medical Splint. *Cailiao Daobao/Mater. Rev.* **2018**, *32*, 1202–1208. [CrossRef]
22. Kelly, S.; Paterson, A.; Bibb, R. A review of wrist splint designs for additive manufacture. In Proceedings of the 2015 14th Rapid Design, Prototyping and Manufacture Conference (RDPM 14), Loughborough, UK, 15–16 December 2015.
23. Fess, E.E. A history of splinting: To understand the present, view the past. *J. Hand Ther.* **2002**, *15*, 97–132. [CrossRef]
24. Valenti, A.; Barsotti, M.; Brondi, R.; Bacciu, D.; Ascari, L. ROS-neuro integration of deep convolutional autoencoders for EEG signal compression in real-time BCIs. In Proceedings of the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Toronto, ON, Canada, 1–14 October 2020; pp. 2019–2024.
25. Hieu, T.C.; Hiep, P.T.; Dinh, H. A study of hierarchical topology and spatial reuse superframe for cluster-based WBAN. In Proceedings of the 2019 6th NAFOSTED Conference on Information and Computer Science (NICS), Hanoi, Vietnam, 12–13 December 2019; pp. 410–415.
26. Hu, F.; Wang, S.; Du, Y.; Deng, Y. An energy-efficiency index based on death probability for maximizing WBAN reward. *Int. J. Electron. Lett.* **2017**, *5*, 261–271. [CrossRef]
27. Qiu, Y.; Haley, D.; Chan, T.; Davis, L. Game theoretic framework for studying WBAN coexistence: 2-Player game analysis and n-player game estimation. In Proceedings of the 2016 Australian Communications Theory Workshop (AusCTW), Melbourne, Australia, 20–22 January 2016; pp. 53–58.
28. Hiep, P.; Kohno, R. Optimizing Packet Generation Rate for Multiple Hops WBAN with CSMA/CA Based on IEEE802.15.6. *Commun. Netw.* **2014**, *6*, 112–123. [CrossRef]
29. Samanta, A.; Misra, S. Energy-efficient and distributed network management cost minimization in opportunistic wireless body area networks. *IEEE Trans. Mob. Comput.* **2017**, *17*, 376–389. [CrossRef]

30. Ahmed, O.; Ren, F.; Hawbani, A.; Al-Sharabi, Y. Energy optimized congestion control-based temperature aware routing algorithm for software defined wireless body area networks. *IEEE Access* **2020**, *8*, 41085–41099. [CrossRef]
31. Xu, S.; Wang, X.; Yang, G.; Ren, J.; Wang, S. Routing optimization for cloud services in SDN-based Internet of Things with TCAM capacity constraint. *J. Commun. Netw.* **2020**, *22*, 145–158. [CrossRef]
32. Vambe, W.T.; Sibanda, K. A fog computing framework for quality of service optimisation in the internet of things (iot) ecosystem. In Proceedings of the 2020 2nd International Multidisciplinary Information Technology and Engineering Conference (IMITEC), Kimberley, South Africa, 25–27 November 2020; pp. 1–8.
33. Frey, S.; Guermandi, M.; Benatti, S.; Kartsch, V.; Cossettini, A.; Benini, L. BioGAP: A 10-core FP-capable ultra-low power IoT processor, with medical-grade AFE and BLE connectivity for wearable biosignal processing. In Proceedings of the 2023 IEEE International Conference on Omni-layer Intelligent Systems (COINS), Berlin, Germany, 23–25 July 2023; pp. 1–7.
34. Kim, D.U.; Lee, J.; Kim, M.; Kim, J.; Lee, J.; Heo, D.; Kim, S.P. The Effect of Wireless Communication Interference on Wireless BCI. In Proceedings of the 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Republic of Korea, 20–22 February 2023; pp. 1–4.
35. Zhou, T.; Mei, Z.; Zhu, X.; Huang, Z. Synchrony detection of epileptic eeg signals based on attention and pearson's correlation coefficient. In Proceedings of the 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Chengdu, China, 17–19 October 2020; pp. 531–535.
36. Banville, H.; Albuquerque, I.; Hyvärinen, A.; Moffat, G.; Engemann, D.A.; Gramfort, A. Self-supervised representation learning from electroencephalography signals. In Proceedings of the 2019 IEEE 29th International Workshop on Machine Learning for Signal Processing (MLSP), Pittsburgh, PA, USA, 13–16 October 2019; pp. 1–6.
37. Jindal, K.; Upadhyay, R.; Singh, H.S. A novel EEG channel selection and classification methodology for multi-class motor imagery-based BCI system design. *Int. J. Imaging Syst. Technol.* **2022**, *32*, 1318–1337. [CrossRef]
38. Li, X.; Ma, Y.; Zhang, Q.; Gao, Y. EEG characteristics extraction and classification based on R-CSP and PSO-SVM. In Proceedings of the 10th International Conference on Computer Engineering and Networks, Xi'an, China, 16–18 October 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 1658–1667.
39. Lee, J.; Chung, W. Motor Imagery Classification using local region CSP features with high-gamma band. In Proceedings of the 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Republic of Korea, 22–24 February 2021; pp. 1–4.
40. Lou, H.; Ye, Z.; Yao, L.; Zhang, Y. Less Is More: Brain Functional Connectivity Empowered Generalizable Intention Classification With Task-Relevant Channel Selection. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2023**, *31*, 1888–1899. [CrossRef]
41. Wang, J.; Shi, L.; Wang, W.; Hou, Z.G. Efficient brain decoding based on adaptive eeg channel selection and transformation. *IEEE Trans. Emerg. Top. Comput. Intell.* **2022**, *6*, 1314–1323. [CrossRef]
42. Keerthika, P.; Sivachitra, M.; Bala, M.P. Eye state EEG signal classification using complex valued neural classifiers. In Proceedings of the 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), Coimbatore, India, 17–18 March 2017; pp. 1–4.
43. Jingwei, L.; Yin, C.; Weidong, Z. Deep learning EEG response representation for brain computer interface. In Proceedings of the 2015 34th Chinese Control Conference (CCC), Hangzhou, China, 28–30 July 2015; pp. 3518–3523.
44. Swee, S.K.; You, L.Z. Fast fourier analysis and EEG classification brainwave controlled wheelchair. In Proceedings of the 2016 2nd International Conference on Control Science and Systems Engineering (ICCSSE), Singapore, 27–29 July 2016; pp. 20–23.
45. Shobana, M.G.; Sajitha, S.; Abirami, S. Brain Computer Interface using EEG Signal for Actuating a 3 DOF Robotic Arm. In Proceedings of the 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 20–22 January 2022; pp. 637–640.
46. Shankhdhar, A.; Mangla, A.; Singh, A.K.; Srivastava, A. Operating of a Drone Using Human Intent Recognition and Characteristics of an EEG Signal. In Proceedings of the 2020 Sixth International Conference on Parallel, Distributed and Grid Computing (PDGC), Waknaghat, India, 6–8 November 2020; pp. 324–327.
47. Emara, H.M.; El-Shafai, W.; Algarni, A.D.; Soliman, N.F.; Abd El-Samie, F.E. A Hybrid Compressive Sensing and Classification Approach for Dynamic Storage Management of Vital Biomedical Signals. *IEEE Access* **2023**, *11*, 108126–108151. [CrossRef]
48. Rivera-Flor, H.; Gurve, D.; Floriano, A.; Delisle-Rodriguez, D.; Mello, R.; Bastos-Filho, T. CCA-based compressive sensing for SSVEP-based brain-computer interfaces to command a robotic wheelchair. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 1–10. [CrossRef]
49. Kumar, G.; Chatterjee, B.; Sen, S. CS-audio: A 16 pJ/b 0.1–15 Mbps compressive sensing IC with DWT sparsifier for audio-AR. *IEEE J. Solid-State Circuits* **2022**, *57*, 2220–2235.
50. Bertrand, A. Distributed signal processing for wireless EEG sensor networks. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2015**, *23*, 923–935. [CrossRef]
51. Musluoglu, C.A.; Bertrand, A. Distributed adaptive trace ratio optimization in wireless sensor networks. *IEEE Trans. Signal Process.* **2021**, *69*, 3653–3670. [CrossRef]
52. Musluoglu, C.A.; Bertrand, A. Distributed trace ratio optimization in fully-connected sensor networks. In Proceedings of the 2020 28th European Signal Processing Conference (EUSIPCO), Amsterdam, The Netherlands, 18–21 January 2021; pp. 1991–1995.
53. Kordestani, M.; Dehghani, M.; Moshiri, B.; Saif, M. A new fusion estimation method for multi-rate multi-sensor systems with missing measurements. *IEEE Access* **2020**, *8*, 47522–47532. [CrossRef]

54. Jamalullah, S.R.; Gladence, L.M. Implementing clustering methodology by obtaining centroids of sensor nodes for human brain functionality. In Proceedings of the 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 6–7 March 2020; pp. 1107–1110.
55. Jagadish, B.; Kiran, M.S.; Rajalakshmi, P. A novel system architecture for brain controlled IoT enabled environments. In Proceedings of the 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom), Dalian, China, 12–15 October 2017; pp. 1–5.
56. Hassani, A.; Plata-Chaves, J.; Bahari, M.H.; Moonen, M.; Bertrand, A. Multi-task wireless sensor network for joint distributed node-specific signal enhancement, LCMV beamforming and DOA estimation. *IEEE J. Sel. Top. Signal Process.* **2017**, *11*, 518–533. [CrossRef]
57. Strypsteen, T.; Bertrand, A. Bandwidth-efficient distributed neural network architectures with application to neuro-sensor networks. *IEEE J. Biomed. Health Inform.* **2022**, *27*, 933–943. [CrossRef] [PubMed]
58. Yao, Q.; Gu, H.; Wang, S.; Li, X. A feature-fused convolutional neural network for emotion recognition from multichannel EEG signals. *IEEE Sens. J.* **2022**, *22*, 11954–11964. [CrossRef]
59. Zhen, C.; Changhui, L. Music audio sentiment classification based on CNN-BiLSTM and attention model. In Proceedings of the 2021 4th International Conference on Robotics, Control and Automation Engineering (RCAE), Wuhan, China, 4–6 November 2021; pp. 156–160.
60. Deepak, S.; Prasad, B. Music Classification based on Genre using LSTM. In Proceedings of the 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 15–17 July 2020; pp. 985–991.
61. Schlögl, A.; Lee, F.; Bischof, H.; Pfurtscheller, G. Characterization of four-class motor imagery EEG data for the BCI-competition 2005. *J. Neural Eng.* **2005**, *2*, L14. [CrossRef] [PubMed]
62. Lee, H.K.; Choi, Y.S. A convolution neural networks scheme for classification of motor imagery EEG based on wavelet time-frequecy image. In Proceedings of the 2018 International Conference on Information Networking (ICOIN), Chiang Mai, Thailand, 10–12 January 2018; pp. 906–909.
63. Yao, Z.; Liu, X. A cnn-transformer deep learning model for real-time sleep stage classification in an energy-constrained wireless device. In Proceedings of the 2023 11th International IEEE/EMBS Conference on Neural Engineering (NER), Baltimore, MD, USA, 24–27 April 2023; pp. 1–4.
64. Nguyen, H.T.; Mai, N.D.; Lee, B.G.; Chung, W.Y. Behind-the-Ear EEG-based Wearable Driver Drowsiness Detection System using Embedded Tiny Neural Networks. *IEEE Sens. J.* **2023**, *23*, 23875–23892. [CrossRef]
65. Anjum, K.; Pompili, D. Anisotropic Diffusion-based Analog CNN Architecture for Continuous EEG Monitoring. In Proceedings of the 2023 IEEE 20th International Conference on Mobile Ad Hoc and Smart Systems (MASS), Toronto, ON, Canada, 25–27 September 2023; pp. 195–203.
66. Ahmed, F.; Iqbal, H.; Nouman, A.; Maqbool, H.F.; Zafar, S.; Saleem, M.K. A non Invasive Brain-Computer-Interface for Service Robotics. In Proceedings of the 2023 3rd International Conference on Artificial Intelligence (ICAI), Islamabad, Pakistan, 22–23 February 2023; pp. 142–147.
67. Ammar, H.; Shrara, H.; Nassereddine, M.; Charara, J.; Sbeity, F. An EEG Study of the Student's Confusion Using Deep Learning. In Proceedings of the 2023 Seventh International Conference on Advances in Biomedical Engineering (ICABME), Beirut, Lebanon, 12–13 October 2023; pp. 121–124.