

Artificial Intelligence and Deep Learning in Medical and Assistive Technologies: Advances, Challenges, and Future Directions

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1. Introduction

Artificial intelligence (AI) and deep learning (DL) have rapidly moved from experimental research to the core of modern medical and assistive technologies. Convolutional neural networks, transformer architectures, and large language models now support tasks such as medical image interpretation, physiological signal analysis, human–machine interaction, and continuous patient monitoring; retrieval-augmented LLMs, in particular, are beginning to reach patient-facing care [1]. This shift is reshaping how clinicians, engineers, and caregivers approach diagnosis, rehabilitation, and daily assistance for people with disabilities or chronic conditions.

However, realizing this potential in practice remains challenging. Clinical and assistive applications must operate under constraints such as limited and imbalanced datasets, the need to generalize across patients and devices, and the demands of real-time, low-power edge deployment. In addition, they must satisfy stringent requirements for interpretability, safety, and ethics—considerations that the literature increasingly frames not as secondary concerns, but as prerequisites for clinical adoption [2]. The contributions to this Special Issue address these challenges from complementary angles, combining methodological innovation with a clear orientation toward real-world impact.

This Special Issue, “Advancements in Medical and Assistive Technologies Using Artificial Intelligence and Deep Learning Techniques,” gathers 17 contributions (14 research articles, 1 review, and 2 systematic reviews) spanning neural signal processing and brain–computer interfaces, medical imaging, cardiovascular diagnostics, assistive and rehabilitation systems, human activity recognition, and the ethical dimensions of deployment. The articles are summarized below, grouped by thematic area; throughout, we situate each cluster against the most recent external state of the art to make the issue’s added value explicit. For clarity, the 17 Special Issue papers are cited throughout as “contribution N” and gathered in the List of Contributions, whereas all other works are cited numerically as [N].

2. Neural Signal Processing and Brain–Computer Interfaces

Two contributions focus on electroencephalography (EEG), a domain in which deep learning has become the dominant decoding paradigm and in which graph-based models, attention/transformer architectures, and data-driven channel selection now define the state of the art [3–5]. Gonzalez-Morales et al. (contribution 1) examine whether inter-channel



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similarity, quantified through Pearson correlation, can guide electrode selection for motor-imagery classification, benchmarking it against a genetic-algorithm strategy on the BCI Competition IV 2a dataset; their findings indicate that data-driven, model-aware selection is preferable for designing efficient, low-channel-count brain–computer interfaces. Gromov et al. (contribution 2) propose a deep learning pipeline for the automated analysis of sleep spindles in epilepsy, showing that AI-quantified spindle morphology and frequency can serve as a reliable biomarker of thalamocortical dysfunction and support faster diagnosis, complementing recent work that exploits sleep-state EEG dynamics to localize epileptogenic activity [6].

3. Artificial Intelligence in Medical Imaging

Medical imaging is the most active application area in this Special Issue, reflecting the broader migration from conventional CNNs toward vision transformers (ViT) and equivariant-geometric architectures for segmentation and classification [7–10]. In neuro-oncology, Lopez-Ramirez et al. (contribution 3) introduce a multiscale ConvNeXt-based U-Net with reverse-attention skip connections for brain-tumor segmentation, achieving strong Dice similarity coefficients across the BraTS 2021–2024 datasets. Gomez-Guzman et al. (contribution 4) benchmark pre-trained CNNs and transformer architectures for multi-class brain-tumor classification on MRI, reaching an accuracy above 99% and demonstrating real-time inference on embedded AI platforms (Jetson AGX Xavier and Orin Nano), underscoring the feasibility of edge-based clinical deployment.

Beyond the brain, Attallah (contribution 5) integrates multiscale deep features from compact CNNs with feature selection for lung- and colon-cancer histopathology, attaining high accuracy with a markedly reduced feature set well suited to computer-aided diagnosis, in line with transfer-learning approaches that have set strong baselines on this task [11]. Shukla et al. (contribution 6) propose HybridFusionNet, which combines vision transformers with attention mechanisms for multi-stage diabetic retinopathy detection, addressing one of the leading causes of preventable visual impairment worldwide; the rapid progress of ViT-based grading [12], and even multimodal LLMs now being benchmarked on fundus images [13], situate this contribution at an active frontier. Complementing these primary studies, Abou Ghayda et al. (contribution 7) review a decade of progress in artificial intelligence for the diagnosis and prognosis of osteosarcoma, synthesizing how machine and deep learning models trained on radiological and histopathological data [14] are reshaping the assessment of this aggressive bone tumor while outlining the methodological gaps that still limit clinical adoption.

4. Cardiovascular Signal Analysis

Cardiac diagnostics are represented by two complementary studies, set against rapid progress in deep learning for phonocardiography and electrocardiography [15–17]. Orozco-Reyes et al. (contribution 8) classify heart sounds by fusing short-time Fourier, mel-scale, and wavelet synchrosqueezed representations, raising accuracy to nearly 99% across public phonocardiogram datasets, echoing the strong performance of spectrogram-based frameworks for heart-sound classification [15]. Prathom et al. (contribution 9) present a preprocessing-free CNN for arrhythmia classification from ECG images, using multi-cycle inputs and a focal-loss function to mitigate class imbalance and improve generalization to previously unseen patients, an imbalance-aware strategy that mirrors recent representation-learning and lightweight-CNN advances in ECG analysis [16,17].

5. Assistive and Rehabilitation Technologies

A central theme of this Special Issue is technology that directly assists people in daily life. Habib et al. (contribution 10) present a lightweight, skeleton-based hand-gesture-recognition framework with an ensemble multi-stream CNN that achieves real-time performance on consumer-grade devices, supporting human–computer interaction and assistive systems, consistent with the move toward graph- and attention-based skeleton models for gesture recognition [18]. Garcia-Herraiz et al. (contribution 11) describe a low-cost, non-intrusive pressure-mat system that uses a CNN to detect infant body position for Sudden Infant Death Syndrome prevention, with autonomous local inference on a Raspberry Pi platform; non-contact infant sleep-safety monitoring is an emerging direction in this space [19].

Targeting mobility and rehabilitation, Lim et al. (contribution 12) predict foot placement and step height from stereo vision enhanced by ground-object awareness, improving the control of walking-assistive systems on uneven terrain, paralleling advances in learning-based estimation for lower-limb exoskeleton control [20]. Farias et al. (contribution 13) develop an LLM-based chatbot to promote adherence to exercise-based treatment in knee osteoarthritis, integrating retrieval-augmented generation and chain-of-thought reasoning to deliver evidence-based, hallucination-mitigated guidance for patients, an approach aligned with disease-specific RAG chat interfaces [21] and with the broader effort to benchmark and safeguard clinical foundation models [22]. Extending assistive monitoring to everyday settings, Mekruksavanich and Jitpattanakul (contribution 14) introduce a multiscale hybrid-attention temporal network that recognizes motionless activities from smartphone inertial sensors, improving the detection of stationary states that are notoriously difficult for wearable human activity recognition systems in assisted-living scenarios; multisensory and transformer-based HAR continue to push this frontier [23,24]. Finally, Castillo Perez et al. (contribution 15) reformulate assistive emotion recognition for children with Down syndrome using Hilbert space-filling curves, which preserve spatial locality when image data are flattened and yield more accurate affective computing models than conventional raster-scan representations, thereby contributing to the wider field of multimodal emotion recognition [25].

Collectively, these contributions connect with a fast-moving external literature on assistive and rehabilitation technology. Recent efforts have begun to codify how such systems should be conceived, proposing principles-based frameworks for the responsible design of AI-enabled assistive technology [26] and surveying the cutting-edge tools now available to protect the wellbeing and safety of older adults [27]. Robotics and intelligent algorithms are, in parallel, reshaping physical rehabilitation: examples range from robot-assisted recovery of motor function after stroke [28] to IoT-enabled platforms that are transforming orthopedic surgery and post-operative care [29]. Intelligent anatomical recognition is extending robotic assistance further into procedural medicine, as illustrated by emerging airway-management systems [30]. Set against this backdrop, the assistive contributions gathered here offer concrete, deployable solutions that are typically low-cost and run locally on edge hardware, with a clear patient-centered focus, helping to translate these broader trends into everyday clinical and home care.

6. Systematic Reviews, Ethics, and Translational Considerations

Two systematic reviews close this Special Issue by broadening its perspective from individual systems to the wider clinical context. Perna et al. (contribution 16) survey the role of artificial intelligence in the detection and diagnosis of neurocognitive disorders, showing how machine and deep learning models can help flag mild cognitive impairment and subjective cognitive decline years before overt dementia, while cautioning that

heterogeneous datasets and limited external validation still constrain translation; these concerns are echoed across systematic reviews of ML/DL for cognitive decline and explainable Alzheimer's classification [31–33]. Technological progress must also be accompanied by careful consideration of real-world implementation. Gkiolnta et al. (contribution 17) examine the challenges and ethical considerations associated with deploying assistive technologies in healthcare, highlighting issues such as data privacy, algorithmic bias, regulatory gaps, and the need for transparent accountability mechanisms to preserve patient trust; these concerns are increasingly formalized in the literature on bias mitigation and governance of clinical AI [34,35]. Read side by side, these two reviews make clear that clinical adoption depends as much on governance, evidence, and ethics as on algorithmic performance.

7. Conclusions and Perspectives

Taken together, the contributions to this Special Issue illustrate several converging trends. Transformer architectures and pre-trained models are increasingly complementing or replacing conventional CNNs [7,9]; edge and embedded AI is enabling real-time, low-cost deployment close to the patient; and large language models are beginning to enter patient-facing care [1,22]. Wearable and vision-based systems are extending assistive monitoring and human activity recognition into everyday environments [23,24], while the systematic reviews gathered here map the diagnostic landscape and the ethical conditions for responsible deployment [2,34]. Across imaging, biosignals, and assistive systems, recurring challenges remain, including limited and imbalanced datasets, generalization to unseen patients and devices, and the need for interpretability and rigorous clinical validation.

We hope that this collection stimulates further interdisciplinary work bridging engineering, clinical practice, and ethics, and that it supports the responsible translation of AI- and DL-based medical and assistive technologies from the laboratory to everyday care.

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