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A Review of Ultra-Low-Power Wearable Technologies for ECG, EEG, and EMG Monitoring

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Abstract
Continuous, unobtrusive acquisition of biopotential signals outside the clinic has become one of the defining ambitions of modern biomedical engineering. Electrocardiography (ECG), electroencephalography (EEG), and electromyography (EMG) each carry diagnostically rich information about cardiac, neural, and neuromuscular function, yet all three have historically depended on bulky, mains-powered instrumentation confined to hospitals and laboratories. Over the past decade, advances in low-voltage analog circuit design, aggressive digital power gating, embedded machine learning, and body-worn energy harvesting have collectively made it plausible to acquire these signals for days or weeks from a device weighing only a few grams. This review examines the technological foundations that make such ultra-low-power operation possible. It surveys electrode technologies and analog front-end architectures that reduce acquisition power into the microwatt regime while preserving the input-referred noise and common-mode rejection required for clinical utility; embedded processing strategies, including event-driven and neuromorphic classifiers, that suppress radio activity by transmitting decisions rather than raw waveforms; wireless communication protocols and duty-cycling schemes that dominate the system energy budget in most practical designs; and harvesting and power-management approaches that point toward battery-free or self-sustaining operation. Three comparative tables consolidate reported performance figures across representative front-ends, embedded classifiers, and energy sources. The review concludes that the field has largely solved the acquisition problem at the circuit level, and that the remaining bottlenecks are systemic: motion artifact robustness, electrode–skin stability over long deployments, the mismatch between harvested and demanded power, and the absence of standardized reporting that would allow fair comparison across published designs.

Keywords: wearable sensors, biopotential acquisition, ultra-low-power circuits, ECG, EEG, EMG, energy harvesting, edge computing

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1. Introduction

1.1 Biopotential Signals in Continuous Health Monitoring

Biopotentials are the small time-varying voltages generated by the coordinated electrical activity of excitable tissue, and they remain the most direct non-invasive window available into the function of the heart, brain, and skeletal muscle. The electrocardiogram reflects the depolarization and repolarization sequence of cardiac myocytes and typically presents at the body surface with amplitudes of roughly 0.5 to 4 mV within a bandwidth of about 0.05 to 150 Hz. The electroencephalogram, by contrast, is attenuated by the skull and scalp to amplitudes on the order of 10 to 100 µV across a bandwidth conventionally spanning 0.5 to 45 Hz, although high-frequency oscillations of clinical interest extend well beyond this range. Surface electromyography occupies an intermediate position, with amplitudes from tens of microvolts to several millivolts and a usable bandwidth reaching 500 Hz or more, since the information of interest lies in the recruitment and firing statistics of motor units rather than in a stereotyped waveform morphology.

The clinical value of these signals depends heavily on the duration over which they are recorded. Paroxysmal atrial fibrillation, transient ischemic events, focal seizures, and fatigue-related changes in muscle activation are all intermittent phenomena that a short in-clinic recording is statistically unlikely to capture. Ambulatory monitoring addresses this directly, and the evidence base for extended-duration recording has grown steadily as the enabling hardware has matured (Guk et al., 2019). Beyond diagnosis, continuous biopotential acquisition underpins closed-loop applications such as myoelectric prosthesis control, where EMG serves as the command channel for a robotic limb (Benatti et al., 2017), and brain–machine interfaces, where EEG features are decoded into intent in real time (Ingolfsson et al., 2020). In each of these cases the sensing hardware is not an accessory to the application but its rate-limiting component.

1.2 From Clinical Instrumentation to Wearable Platforms

The migration of biopotential recording from the laboratory bench to the body has followed a fairly consistent trajectory across all three modalities. Early ambulatory systems, exemplified by the Holter monitor, were essentially miniaturized versions of clinical instruments: they used the same wet gel electrodes, the same discrete instrumentation amplifiers, and stored data locally for later offline review. The transition to genuinely wearable systems required simultaneous progress on three fronts, namely the electrode interface, the integration density of the electronics, and the form factor of the power source. Casson (2019) traced this progression for EEG in particular, noting that the modality's move out of the laboratory has been slower than that of ECG precisely because its far smaller signal amplitudes leave less tolerance for the compromises that miniaturization imposes.

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Electrode development has moved away from silver/silver-chloride wet electrodes, which offer excellent impedance characteristics but degrade as the gel dehydrates and frequently provoke skin irritation over multi-day wear. Dry electrodes, fabricated from conductive polymers, textiles, metal-coated pillars, or carbon composites, tolerate long deployments but present contact impedances one to two orders of magnitude higher, which imposes correspondingly stricter requirements on front-end input impedance (Shad et al., 2020). Capacitive and non-contact electrodes go further still by removing the requirement for galvanic contact entirely, allowing sensing through clothing at the cost of severe sensitivity to displacement and triboelectric charge (Sun & Yu, 2016).

In parallel, the electronics have compressed from multi-board systems into single-chip solutions. Contemporary biomedical systems-on-chip integrate the instrumentation amplifier, programmable gain and filtering, analog-to-digital conversion, a digital signal processor, and power management within a few square millimetres of silicon (Van Helleputte et al., 2015; Konijnenburg et al., 2016). Flexible and stretchable substrates have extended this integration to conformal patches that mechanically match skin, reducing motion artifact by minimizing relative movement at the interface (Iqbal et al., 2021). The result is a class of devices that are worn rather than carried, and that are consequently expected to operate without intervention for periods measured in days or weeks.

1.3 Energy as the Defining Design Constraint

For a wearable biopotential system, energy is not one design consideration among many but the constraint from which nearly all others derive. A device intended for continuous wear must be small and light, which caps the volume available for a battery; a typical coin cell or small lithium-polymer pack in a chest patch or ear-worn device offers on the order of 10 to 100 mAh. Achieving a week of operation from such a source implies an average system current in the tens of microamperes, a budget that must cover electrode biasing, amplification, digitization, computation, and radio activity combined.

The distribution of that budget is frequently counterintuitive. Analog acquisition, despite being the most technically demanding block to design, is rarely the dominant consumer in a well-optimized system. Reported multi-channel front-ends achieve total acquisition power in the range of a few microwatts to a few hundred microwatts, including on-chip digitization and some degree of motion-artifact reduction (Van Helleputte et al., 2015). Wireless transmission, by contrast, routinely accounts for the majority of system energy when raw waveforms are streamed continuously, because the radio must be active in proportion to the data volume produced (Tosi et al., 2017). This asymmetry has driven the central architectural insight of the field: reducing the quantity of data that leaves the node is generally more effective than reducing the cost of producing it.

That insight motivates the shift toward on-node computation. If a classifier running locally can convert a continuous EEG stream into an intermittent seizure alert, or an ECG stream into a beat-level arrhythmia label, then the radio duty cycle collapses by orders of magnitude even though the processor's own consumption rises modestly (Sopic et al., 2018). The trade-off is favourable only when the local computation is itself efficient, which has stimulated interest in event-driven, spiking, and quantized network architectures specifically shaped to the arithmetic capabilities of microcontroller-class hardware (Amirshahi & Hashemi, 2019).

1.4 Scope and Structure of the Review

This review is concerned with the technologies that enable microwatt- to milliwatt-scale operation of wearable systems acquiring ECG, EEG, and EMG. It treats these three modalities together because, despite their differing amplitude and bandwidth requirements, they share a common signal chain and confront the same energy economics. Work on photoplethysmography, bioimpedance, and electrochemical sweat sensing is referenced only where it informs the biopotential case, most notably in multimodal systems-on-chip and in energy harvesting.

The literature review that follows is organized around the four layers of the signal chain where power is spent or saved. Section 2.1 addresses the electrode interface and the analog front-end. Section 2.2 examines digital processing and embedded intelligence. Section 2.3 covers wireless communication and system-level power management. Section 2.4 surveys energy harvesting and self-powered operation. Three tables consolidate quantitative comparisons across representative implementations. The review closes with a synthesis of the current state of the art and an assessment of the directions in which further progress appears both necessary and feasible.

2. Literature Review

2.1 Electrodes and Analog Front-End Architectures

The analog front-end (AFE) sets the ceiling on what any downstream processing can achieve, since information destroyed at the input cannot be recovered. Its design is a negotiation among four quantities that resist simultaneous optimization: input-referred noise, input impedance, common-mode rejection ratio (CMRR), and power consumption. Thermal noise in a MOSFET-based amplifier scales inversely with transconductance, which in weak inversion scales linearly with bias current; consequently, halving the input-referred noise of a given topology costs roughly a factor of four in current. This relationship, captured by the noise efficiency factor (NEF) and its power-normalized variant (PEF), is the fundamental figure of merit against which biopotential amplifiers are compared.

The requirements differ substantially by modality. An EEG channel must resolve signals of a few microvolts, and so demands input-referred noise below approximately 1 µVrms over the 0.5–100 Hz band. An ECG channel, with millivolt-scale inputs, tolerates noise an order of magnitude higher and can therefore be operated at markedly lower bias current. EMG channels

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sit between the two but require wider bandwidth, which raises the integrated noise for a given noise density and pushes designers toward higher bias currents than the amplitude alone would suggest.

Capacitively coupled chopper instrumentation amplifiers have become the dominant topology. Chopping modulates the input signal to a frequency above the 1/f corner of the input devices, amplifies it there, and demodulates it back to baseband, thereby removing flicker noise and input offset that would otherwise swamp low-frequency biopotentials. Capacitive input coupling blocks the electrode half-cell potential, which can reach several hundred millivolts and would saturate a DC-coupled amplifier. The residual difficulty is that chopping lowers the input impedance seen by the electrode, since the switching capacitors draw charge from the source at the chopping frequency. Positive-feedback impedance boosting and pre-charging techniques mitigate this, and are essentially mandatory when dry electrodes with contact impedances in the hundreds of kilohms to megohms are used (Shad et al., 2020).

Active electrodes address the same problem from the other direction by placing a buffer or preamplifier physically at the electrode site, so that the high-impedance node is confined to a millimetre-scale interconnect rather than a long cable susceptible to capacitive pickup and triboelectric noise. Xu et al. (2017) provide a systematic design methodology for wearable EEG active electrodes, showing that the local buffer's own power consumption is a small penalty relative to the reduction in motion-induced interference, and that careful attention to the DC bias path is required to avoid trading one instability for another. Non-contact capacitive electrodes extend this approach to sensing through fabric, though the very high and variable source impedance makes them substantially more sensitive to displacement (Sun & Yu, 2016).

At the system level, integration has proven at least as important as amplifier-level optimization. Van Helleputte et al. (2015) reported a multi-sensor biomedical SoC combining three ECG channels, a bio-impedance readout, motion-artifact reduction based on the measured impedance, and an integrated DSP, consuming 345 µW in total. Konijnenburg et al. (2016) extended this line of work to a system integrating synchronized ECG, bio-impedance, galvanic skin response, and dual photoplethysmography readouts alongside power management and LED drivers on a single die. The significance of such designs lies less in any single record-setting metric than in the demonstration that a complete acquisition subsystem, including artifact compensation, can be delivered within a budget that a coin cell can sustain for weeks.

Motion artifact deserves particular emphasis because it is the principal reason that laboratory-grade performance does not translate to ambulatory settings. Mechanical disturbance of the electrode–skin interface produces baseline excursions that are far larger than the signal itself and that overlap it spectrally, which places them beyond the reach of conventional filtering. Adaptive cancellation using a simultaneously measured reference, typically electrode–skin impedance or

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accelerometry, is the most effective countermeasure and is now commonly integrated on-chip (Van Helleputte et al., 2015). For EEG, artifact contamination is compounded by ocular and muscular sources, and a substantial literature addresses their detection and removal, though most of the more capable methods remain too computationally demanding for on-node execution (Islam et al., 2016).

Table 1. Representative ultra-low-power biopotential acquisition front-ends and systems-on-chip

Reference	Modality	Architecture	Reported power	Notable feature
Van Helleputte et al. (2015)	ECG + bio-impedance	Multi-channel SoC with integrated DSP	345 µW (full system)	On-chip impedance-based motion artifact reduction
Konijnenburg et al. (2016)	ECG, bio-Z, GSR, PPG	Multimodal SoC with power management	Sub-milliwatt per active mode	Synchronized multi-sensor acquisition on one die
Xu et al. (2017)	EEG	Active electrode with local buffer	Tens of µW per electrode	Cable and triboelectric noise suppression
Shad et al. (2020)	EEG	Passive vs. active dry electrode comparison	Electrode-dependent	Systematic impedance and noise characterization
Sun & Yu (2016)	ECG / EEG	Capacitive non-contact electrode	Application-dependent	Sensing through clothing without galvanic contact
Dieffenderfer et al. (2016)	ECG + environmental	Integrated wearable monitoring platform	Milliwatt-scale system	Multi-day chronic disease monitoring deployment

2.2 Low-Power Digital Processing and On-Node Intelligence

Once a signal has been digitized, the system faces a decision with dominant energy consequences: transmit the samples, or interpret them locally. Continuous streaming of a single ECG channel at 250 Hz and 12-bit resolution produces roughly 3 kbit/s of payload, which is modest in absolute terms but demands frequent radio activity. A multi-channel EEG montage at 256 Hz across 16 channels produces well over 50 kbit/s, at which point the radio becomes the

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overwhelming consumer. Local processing inverts this arithmetic by replacing a continuous stream with sparse, semantically dense output.

The simplest form of local processing is compression. Lossless schemes exploiting the predictability of quasi-periodic waveforms achieve useful ratios without diagnostic risk, while compressed sensing acquires a reduced number of random projections directly, shifting reconstruction cost to the receiver. Compressed sensing is attractive because it lowers both sampling and transmission energy, but its reconstruction guarantees depend on sparsity assumptions that hold well for ECG and less reliably for EMG, whose stochastic character resists sparse representation.

More consequential is the move to on-node classification. Sopic et al. (2018) demonstrated an event-driven approach to myocardial infarction detection in which a lightweight screening stage runs continuously and a more expensive classification stage is invoked only when the screening stage flags a candidate event. This hierarchical arrangement exploits the fact that pathological events are rare: the expensive computation, and any subsequent transmission, is amortized over long quiescent intervals. The same principle applies broadly, and variants appear in seizure detection, arrhythmia screening, and gesture recognition.

Neuromorphic and spiking approaches take event-driven processing to its logical conclusion by making the representation itself sparse. Amirshahi and Hashemi (2019) developed an ECG classification algorithm using spike-timing-dependent plasticity and its reward-modulated variant, targeting real-time operation on ultra-low-power wearable hardware. Because computation is triggered only by spike events rather than by a fixed clock, activity scales with signal content, and long stretches of unremarkable rhythm consume correspondingly little energy. The approach also supports a degree of on-device adaptation to individual morphology, which is valuable given the substantial inter-subject variability of biopotential signals.

Conventional deep learning has been adapted to the constraint through architectural economy rather than through novelty of computational paradigm. Ingolfsson et al. (2020) introduced EEG-TCNet, a temporal convolutional network for motor-imagery decoding whose parameter count and memory footprint were deliberately bounded so as to fit within microcontroller-class resources while maintaining competitive classification accuracy. Zanghieri et al. (2020) applied a comparable philosophy to surface EMG, deploying a temporal convolutional network on a multicore parallel IoT processor and reporting real-time gesture recognition at an energy cost per inference low enough for a battery-powered prosthetic controller. Xiong et al. (2021) surveyed the broader landscape of deep learning for EMG-based human–machine interaction, and observed that the reported accuracy advantage of deep models over well-engineered classical feature sets narrows considerably once the comparison is constrained to models that actually fit on embedded hardware.

That observation matters. Classical pipelines based on time-domain features such as mean absolute value, zero crossings, waveform length, and slope sign changes, followed by a linear discriminant or support vector classifier, remain highly competitive for EMG gesture recognition and consume a small fraction of the energy of any neural network (Benatti et al., 2017). The decision between classical and learned approaches should therefore be framed as an energy–accuracy trade-off rather than as a question of algorithmic sophistication, and in many deployed systems the classical option remains the correct one.

Table 2. Embedded processing and classification approaches for wearable biopotential systems

Reference	Modality	Approach	Target platform	Principal advantage
Sopic et al. (2018)	ECG	Event-driven hierarchical classification	Wearable embedded system	Expensive stage invoked only on candidate events
Amirshahi & Hashemi (2019)	ECG	Spiking network with STDP / R-STDP learning	Ultra-low-power wearable node	Activity scales with signal content; on-device adaptation
Ingolfsson et al. (2020)	EEG	Temporal convolutional network (EEG-TCNet)	Microcontroller-class hardware	Small memory footprint at competitive accuracy
Zanghieri et al. (2020)	EMG	Temporal convolutional network	Multicore parallel IoT processor	Real-time gesture recognition within battery budget
Benatti et al. (2017)	EMG	Classical time-domain features + linear classifier	Body-area controller	Very low computational cost; prosthesis-ready latency
Xiong et al. (2021)	EMG	Survey of deep learning methods	Various	Comparative assessment of accuracy versus deployability

2.3 Wireless Communication and System-Level Power Management

In systems that transmit any appreciable volume of data, the radio dominates the energy budget, and its optimization is largely a matter of minimizing time spent active rather than reducing instantaneous power. Bluetooth Low Energy has become the default choice for wearable biopotential devices, primarily because of its universal availability in smartphones, which removes the need for a proprietary gateway. Tosi et al. (2017) reviewed BLE performance systematically and characterized the relationship between connection interval, payload size, throughput, and energy per bit, showing that energy efficiency improves substantially when data are aggregated into larger, less frequent packets rather than transmitted as they are produced. This favours buffering, and the resulting latency is acceptable for monitoring applications though not for closed-loop control.

The alternatives occupy specific niches. Zigbee and other IEEE 802.15.4 derivatives offer mesh networking useful in multi-node body sensor networks but require a dedicated coordinator. Proprietary sub-gigahertz links achieve lower energy per bit through simpler protocol stacks and better propagation, at the cost of interoperability. Ultra-wideband and backscatter approaches shift complexity to the receiver: backscatter in particular can reduce transmitter power by orders of magnitude by modulating an incident carrier rather than generating one, enabling battery-free tags at the expense of requiring an external illuminator and short range.

Beyond protocol choice, system-level power management exploits the fact that most subsystems are idle most of the time. Aggressive duty cycling places the processor and radio in deep sleep between activity windows, with leakage current in the sub-microampere range determining the floor. Dynamic voltage and frequency scaling adjusts the operating point to the instantaneous computational demand. Power gating removes supply from unused blocks entirely, and clock gating from those that must retain state. Because energy per operation in digital logic scales with the square of supply voltage, near-threshold operation offers large savings, though at the cost of increased sensitivity to process and temperature variation and a corresponding need for margin.

Sampling policy also carries direct energy consequences that are frequently underappreciated. Sampling rate determines not only ADC energy but also the volume of data propagating through every downstream block, so oversampling imposes a compounding penalty. Adaptive sampling, in which rate is modulated according to signal activity, exploits the non-stationarity of biopotentials, and level-crossing or asynchronous sampling eliminates the fixed clock entirely by generating samples only when the signal changes by a defined increment. For ECG in particular, where the signal is quiescent between complexes for most of each cardiac cycle, asynchronous schemes can reduce sample counts substantially without diagnostic loss.

Integrated wearable platforms illustrate how these techniques combine in practice. Dieffenderfer et al. (2016) described a low-power system for continuous monitoring of environmental exposure

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and physiological state in chronic respiratory disease, in which sensing, processing, and communication were jointly managed to achieve multi-day operation under realistic use. The general lesson from such deployments is that system lifetime is determined by the interaction of subsystems rather than by the efficiency of any one of them, and that a design optimized block by block will typically underperform one optimized jointly.

2.4 Energy Harvesting and Self-Powered Operation

The logical endpoint of power reduction is a device that never requires recharging. Energy harvesting from the wearer or their environment is the mechanism, and the question is whether the harvested power can meet the demanded power with acceptable reliability. Photovoltaic harvesting offers the highest areal power density of the practical options, with outdoor irradiance supporting figures in the milliwatt-per-square-centimetre range, but indoor illumination reduces this by two to three orders of magnitude and clothing occlusion is common in wearable placements. Thermoelectric generators exploit the gradient between skin and ambient air, producing tens of microwatts per square centimetre under favourable conditions, with output falling sharply as ambient temperature approaches body temperature. Kinetic harvesting from gait and limb motion is intermittent by nature and its yield depends strongly on placement and activity level. Biofuel cells oxidizing lactate in sweat and radio-frequency harvesting from ambient or dedicated transmitters complete the practical set.

Ostfeld et al. (2016) demonstrated a flexible system integrating photovoltaic harvesting with a lithium-ion storage element on a common flexible substrate, establishing that harvester and storage can be co-fabricated in a form factor compatible with wearable use rather than assembled from rigid components. Yin et al. (2021) advanced the concept considerably with a self-sustainable e-textile bioenergy microgrid combining triboelectric and biofuel cell harvesting with supercapacitor storage, showing that heterogeneous sources with complementary temporal availability can be combined to smooth the intermittency that limits any single mechanism. Bandodkar et al. (2019) demonstrated fully battery-free, skin-interfaced systems powered by near-field coupling, which sidesteps harvesting variability entirely at the cost of requiring proximity to a reader.

Two engineering realities constrain all of these approaches. First, harvested power is intermittent, so storage and power-management circuitry are mandatory, and the efficiency of the converter at microwatt input levels frequently dominates end-to-end performance. Boost converters designed for milliwatt operation perform poorly at microwatt inputs, and maximum power point tracking must itself consume negligible power to be worthwhile. Second, the gap between typical harvested power and typical system demand remains real for continuous multi-channel acquisition. Battery-free operation is presently demonstrable for single-channel, low-duty-cycle, or externally powered applications; for continuous multi-channel EEG it remains out of reach, and harvesting in that regime functions as battery life extension rather than replacement. Iqbal et al. (2021) reached a similar conclusion in surveying advances in healthcare wearables, noting that power autonomy consistently lags behind sensing capability across the field.

Table 3. Energy harvesting sources for wearable biopotential systems

Source	Typical harvested power density	Availability	Principal limitation
Photovoltaic (outdoor)	~1–10 mW/cm²	Daylight hours only	Occlusion by clothing; negligible indoors
Photovoltaic (indoor)	~1–10 µW/cm²	Continuous when lit	Very low yield; large area required
Thermoelectric (body heat)	~10–60 µW/cm²	Continuous	Falls sharply in warm ambient conditions
Kinetic / piezoelectric	~1–100 µW/cm²	Intermittent, activity-dependent	Highly placement- and motion-dependent
Biofuel cell (sweat lactate)	~10–100 µW/cm²	During perspiration	Limited operational lifetime; enzyme degradation
RF / near-field coupling	Reader-dependent	On demand	Requires external transmitter in close proximity

Values are indicative ranges compiled from the reviewed literature (Ostfeld et al., 2016; Bandodkar et al., 2019; Yin et al., 2021; Iqbal et al., 2021) and vary substantially with placement and operating conditions.

3. Conclusion

The evidence surveyed here supports a reasonably clear assessment of where ultra-low-power wearable biopotential monitoring currently stands. At the circuit level, the acquisition problem is substantially solved. Chopper-stabilized capacitively coupled instrumentation amplifiers, combined with input impedance boosting and on-chip artifact compensation, deliver noise and CMRR performance adequate for clinical ECG, EEG, and EMG at power levels of microwatts per channel, and complete multimodal acquisition subsystems now operate within a few hundred microwatts (Van Helleputte et al., 2015; Konijnenburg et al., 2016). Further reduction in front-end power would yield diminishing returns, because the AFE is no longer the dominant term in most system budgets.

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The dominant term is communication, and the field's most productive response has been to reduce data volume at the source rather than to make transmission cheaper. Event-driven and hierarchical classification architectures exploit the rarity of clinically significant events to collapse both computation and radio duty cycle (Sopic et al., 2018; Amirshahi & Hashemi, 2019), while compact neural architectures have made learned inference feasible on microcontroller-class hardware for both EEG and EMG (Ingolfsson et al., 2020; Zanghieri et al., 2020). Importantly, well-engineered classical pipelines remain competitive for several tasks at a small fraction of the energy cost, and the choice between paradigms should be made on measured energy-accuracy grounds rather than by default (Benatti et al., 2017; Xiong et al., 2021).

Energy autonomy remains the least mature layer. Harvesting demonstrations are genuinely impressive in isolation, and hybrid multi-source microgrids show a credible path toward smoothing intermittency (Yin et al., 2021), but the arithmetic still does not close for continuous multi-channel acquisition under realistic conditions. Battery-free operation is achievable today for constrained applications, and elsewhere harvesting extends rather than replaces stored energy.

Two cross-cutting weaknesses limit progress. The first is robustness: motion artifact and electrode–skin instability, not circuit noise, determine the quality of ambulatory recordings, and dry electrodes trade comfort and longevity for a considerably harder signal-conditioning problem (Shad et al., 2020; Islam et al., 2016). The second is comparability. Reported power figures are quoted variously per channel or per system, with and without radio, under different bandwidths and duty cycles, which makes fair comparison across publications extremely difficult and obscures whether apparent advances reflect genuine improvement or favourable accounting.

4. Future Work

Several directions appear both necessary and technically tractable, and progress on them would likely have a larger effect on deployed system performance than further optimization of the analog front-end.

Standardized benchmarking and reporting. The field would benefit substantially from an agreed reporting convention specifying total system energy per hour of monitoring under a defined duty cycle, alongside per-channel figures, together with the bandwidth, resolution, and radio configuration assumed. Public datasets recorded with ambulatory rather than laboratory protocols, including realistic motion contamination, would allow embedded classifiers to be compared on the conditions they will actually encounter. Without such conventions, the literature will continue to accumulate results that cannot be meaningfully ranked.

Robust electrode interfaces for long deployments. Sustained multi-week recording requires electrode materials that maintain stable impedance without dehydration, irritation, or

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delamination. Promising directions include conductive hydrogel composites with controlled water retention, textile electrodes with engineered contact geometry, and microneedle arrays that bypass the stratum corneum. Equally important is the co-design of electrode and front-end: an impedance-monitoring channel that continuously characterizes contact quality can drive adaptive gain, adaptive filtering, and channel rejection, converting an unpredictable analog problem into a manageable system-level one.

Analog and mixed-signal preprocessing. Performing feature extraction in the analog domain before digitization avoids paying the ADC and digital energy cost for information that will be discarded. Analog filter banks, mixed-signal correlators, and in-memory computing arrays that perform matrix-vector products at the sensor interface are all plausible routes to reducing the energy of the earliest processing stages by an order of magnitude. The open question is whether the accuracy achievable with analog computation, which is inherently subject to mismatch and drift, is sufficient for clinically consequential decisions.

Adaptive, personalized on-device models. Inter-subject variability in biopotential morphology is large enough that population-trained models frequently underperform for individuals, yet full personalization requires labelled data that individuals cannot supply. On-device incremental learning, few-shot adaptation, and federated schemes that share model updates rather than raw physiological data offer routes to personalization compatible with both the energy budget and privacy expectations. Spiking architectures with local learning rules are particularly well matched to this requirement (Amirshahi & Hashemi, 2019).

Closing the harvesting gap. Progress here depends less on new transduction mechanisms than on the power-conditioning electronics between harvester and load. Converters that maintain high efficiency at single-microwatt inputs, storage elements with low self-discharge and high cycle life in flexible form factors, and energy-aware schedulers that modulate sampling rate and inference frequency according to available energy would together do more than incremental improvements in harvester output. Systems that degrade gracefully — reducing channel count or inference rate rather than shutting down when energy is scarce — represent a design philosophy the field has yet to adopt widely.

Clinical validation at scale. Finally, the great majority of published ultra-low-power systems are validated on small cohorts under controlled conditions. Demonstrating that a device sustaining weeks of autonomous operation produces recordings of genuine diagnostic value, in unsupervised settings and across diverse populations, is the step that would move this technology from engineering achievement to clinical instrument. That validation is a slower and less glamorous undertaking than circuit innovation, but it is the one on which eventual adoption depends.

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