

**Review****Review of applications of artificial intelligence in bioimpedance analysis****Soumyajit Podder^{1,2,3,*}**

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Abstract: Bioimpedance analysis serves as a non-invasive modality for evaluating human body composition and fluid balance. Despite its clinical translational potential, traditional empirical regression models remain vulnerable to physiological variability, demographic heterogeneity, and measurement noise, which inflate estimation error and restrict generalizability. In this review, we present an evidence-based narrative synthesis of artificial intelligence (AI) methodologies integrated into bioimpedance frameworks to investigate these limitations. We analyzed how machine learning algorithms optimize non-linear Cole parameter extraction and equivalent circuit modeling under noisy spectral conditions without requiring rigid baseline assumptions. Furthermore, deep learning architectures such as convolutional networks and physics-informed models were examined for their capacity to resolve ill-posed inverse reconstruction problems in electrical impedance tomography and to process multidimensional sensor streams. Rather than presuming established clinical maturity, we critically scrutinized study-level translational readiness, highlighting pervasive methodological bottlenecks, including the reliance on small, single-center cohorts, risks of data leakage from sample-level cross-validation, hardware-induced motion artifacts, and an absence of independent external multicenter replication. By contextualizing emerging paradigms, including Explainable AI, uncertainty quantification, and decentralized learning within a realistic clinical taxonomy, we outline the methodological and validation standards necessary to advance AI-driven bioimpedance from exploratory proof-of-concept demonstrations toward reproducible, evidence-based clinical evaluation.

Keywords: bioimpedance analysis; artificial intelligence; machine learning; deep learning; electrical impedance tomography; wearable health monitoring

1. Introduction

Bioimpedance analysis (BIA) is a non-invasive, cost-effective diagnostic modality that quantifies the electrical properties of biological tissues to assess human body composition, fluid distribution, and cellular health status [1,2]. By injecting low-amplitude, alternating electrical current into the human body, BIA measures the voltage drop across specific anatomical boundaries to derive tissue resistance (R) and reactance (X_c). Muscle tissue, characterized by a high aqueous volume and rich electrolyte concentrations, exhibits low resistance and superior electrical conductance. Conversely, adipose tissue contains minimal water and acts as an electrical insulator, demonstrating high resistance [3–5]. By leveraging these differential conductivity profiles, BIA facilitates the mathematical estimation of critical physiological compartments. These include total body water (TBW), extracellular water (ECW), and intracellular water (ICW). These derived parameters serve as foundational indicators across a broad spectrum of clinical workflows, ranging from longitudinal nutritional assessments to the optimization of fluid management in critical care settings.

Despite its clinical translational potential, traditional BIA exhibits systemic limitations when deployed in dynamic or heterogeneous populations. Conventional methods rely heavily on empirical linear regression equations that assume a static, uniform hydration state typically fixing fat-free mass (FFM) hydration at a constant 73%. Because these empirical models are calibrated using highly specific, homogenous reference cohorts, their diagnostic accuracy degrades significantly when applied to subjects outside those baselines. In clinical environments, perturbations such as minor core temperature fluctuations, postural fluid shifts, and demographic variations in ethnicity, age, or sex regularly violate these rigid assumptions. Consequently, traditional regression models often introduce estimative errors ranging from 10% to 20% in complex clinical scenarios [6–8].

To overcome these legacy constraints, multi-frequency bioimpedance analysis (MF-BIA) and bioimpedance spectroscopy (BIS) have been developed to scan a broad frequency domain [9,10]. This multi-frequency scanning capability generates high-dimensional, non-linear datasets that capture detailed cellular properties. These properties are quantified through prognostic indicators such as the raw phase angle and the ECW/TBW fluid ratio. In preliminary ambulatory studies, a depressed phase angle serves as a surrogate prognostic indicator of cell membrane degradation, lean muscle wasting, and systemic inflammation. For instance, suppressed phase angles correlate directly with sarcopenic obesity in hemodialysis cohorts, progressive depressive symptomatology in maintenance dialysis, and extended hospital lengths of stay among geriatric inpatients [11–13]. Similarly, abnormalities in the ECW/TBW ratio offer crucial diagnostic insight into subclinical frailty, cardiorespiratory debility in viral sequelae, and latent postpartum metabolic syndrome [14,15]. In pediatric medicine, bioimpedance vector analysis (BIVA) facilitates the tracking of localized hydration disturbances in acute nephrotic syndrome, offering an essential, non-invasive tool for developmental and syndromic tracking [16].

The historical limitation of BIA, however, resides in the mathematical processing of these multidimensional datasets. Traditional statistical models cannot effectively resolve the non-linear, time-varying relationships inherent to multi-frequency tissue relaxation and physiological fluid shifts.

This mathematical bottleneck provides a clear rationale for the integration of artificial intelligence (AI) within the bioimpedance framework. Advanced computational frameworks alter conventional signal post-processing by treating impedance spectra not as isolated data points, but as complex topological feature arrays. Supervised machine learning algorithms, including support vector machines (SVM) and neural networks, bypass iterative physical model inversion by mapping multi-frequency impedance features directly to tissue pathological states and dynamic physiological transitions [17,18]. For spatial conductivity mapping, deep learning (DL) architectures like convolutional neural networks (CNNs) and U-Net variants have refined the spatial resolution of Electrical Impedance Tomography (EIT) [19]. These networks solve the inherently ill-posed inverse problem of image reconstruction, suppressing measurement noise and reducing reconstruction artifacts. For sequential, time-series analysis, recurrent neural networks (RNNs) and long short-term memory (LSTM) blocks model the continuous temporal dynamics of internal fluid shifts, enabling predictive tracking during high-acuity interventions such as hemodialysis.

Furthermore, the synergy between AI and bioimpedance expands multi-parametric monitoring capability by simplifying the integration of multimodal data structures. By fusing raw impedance spectra with complementary physiological data streams, such as tri-axial accelerometry, photoplethysmography (PPG), or electrocardiography (ECG), multimodal AI models formulate a comprehensive, contextualized representation of a patient's real-time functional status [20,21]. This multi-sensor alignment enables mobile wearable devices to isolate movement-induced artifacts from genuine fluid variations. Consequently, it supports the transition of BIS and EIT from stationary, episodic laboratory instruments to continuous, point-of-care medical tracking networks. These personalized analytical models are highly applicable to real-time tissue hydration assessment [22], tissue type differentiation [23], oncology diagnostics [24,25], and end stage kidney failure [26]. Furthermore, integrating AI with wearable bioimpedance architectures expands ambulatory monitoring beyond traditional body composition into metabolic tracking, such as non-invasive glycemic trends [27], automated dietary activity recognition [28], and continuous cuffless hemodynamic monitoring [29].

However, translating AI-enhanced bioimpedance into scalable, clinically validated medical devices requires addressing several outstanding challenges. Pervasive bottlenecks include the small sample sizes of medical datasets, the opaque uninterpretable nature of deep neural networks, and algorithmic biases stemming from a historical lack of demographic diversity in training populations [30]. To establish algorithmic transparency and assist clinical evaluation, Explainable AI (XAI) frameworks such as Shapley Additive Explanations (SHAP) are increasingly utilized to quantify model-based feature attributions, clarifying the relative statistical contribution of individual spectral features to model predictions without presuming underlying causal physiological effects [31]. Decentralized optimization methods, most notably federated learning, offer a viable pathway to train secure, cross-population models across multiple medical centers without compromising patient data privacy [32]. Additionally, generative architectures, including generative adversarial networks (GANs) and variational autoencoders (VAEs), mitigate data scarcity by synthesizing higher spatial resolution synthetic impedance spectra, which expands training data volume while preserving biological realism [33].

In this narrative scoping review, we provide a comprehensive, evidence-based synthesis of contemporary advancements in AI-enhanced human BIA. While medical applications form the core clinical taxonomy of this paper, foundational bioelectrical studies from plant physiology and aquatic

biomass monitoring are strategically incorporated as cross-disciplinary methodological benchmarks for non-linear feature extraction and multi-sensor data alignment. To ensure a representative and technically rigorous literature foundation, an extensive literature survey was conducted across electronic databases, including PubMed/MEDLINE, IEEE Xplore, Scopus, and Web of Science for peer-reviewed studies published up to 2026. The search utilized combinations of primary keywords and Boolean operators: ('bioimpedance' OR 'bioelectrical impedance analysis' OR 'BIA' OR 'electrical impedance tomography' OR 'EIT' OR 'bioimpedance spectroscopy' OR 'BIS') AND ('machine learning' OR 'deep learning' OR 'artificial intelligence' OR 'neural networks' OR 'explainable AI'). Studies were curated based on relevance to human clinical monitoring, body composition assessment, algorithm architecture, and wearable sensor translation, while non-peer-reviewed abstracts, unverified preprints, and non-physiological engineering works lacking medical applicability were excluded [34,35]. By establishing an engineering-grounded framework across these thematic pillars, we examined how computational intelligence may support the evolution of BIA toward proactive, personalized precision health monitoring.

2. Fundamentals of bioimpedance analysis

2.1. Mathematical framework of bioimpedance

BIA quantifies the opposition of biological tissues to an alternating electrical current, encapsulating resistance $R(\omega)$, which arises from ionic conduction within fluid compartments, and reactance $X_c(\omega)$, attributable to the dielectric and capacitive properties of cell membranes [36,37]. The frequency-dependent complex impedance spectrum $Z(\omega)$ is conventionally modeled using the Cole-Cole relaxation model:

$$Z(\omega) = R_\infty + \frac{R_0 - R_\infty}{1 + (j\omega\tau)^\alpha} \quad (1)$$

where $Z(\omega)$ denotes the complex-valued impedance, R_0 represents the low-frequency limit of resistance dominated by ECW conduction paths, R_∞ denotes the high-frequency asymptotic resistance reflecting TBW conduction across fully permeated membrane, $\omega = 2\pi f$ is the angular frequency, τ is the characteristic relaxation-time of the tissue, and α is a dimensionless exponent (ranging from 0 to 1 for biological tissue) characterizing the distribution of relaxation times and structural tissue heterogeneity [38–40]. In this formulation, $\alpha = 1$ simplifies the model to an idealized single-time-constant Debye relaxation, whereas $\alpha < 1$ represents non-ideal, distributed dielectric relaxation typically of complex biological tissues (note that in alternative literature conventions, this dispersion exponent is denoted as $1 - \alpha$).

In equivalent circuit representations, the non-ideal capacitive behavior of the cell membrane is modeled as a constant phase element (CPE) with admittance $Y_{\text{CPE}}(\omega) = Q(j\omega)^\alpha$, where Q is the pseudo-capacitance parameter with fractional dimensions of $\text{F} \cdot \text{s}^{\alpha-1}$ (or $\Omega^{-1} \cdot \text{s}^\alpha$). Under this circuit topology, the characteristic relaxation time is defined dimensionally as:

$$\tau = [(R_0 - R_\infty)Q]^{1/\alpha} \quad (2)$$

Decomposing the complex impedance $Z(\omega) = R(\omega) + jX_c(\omega)$ into its respective real (resistive) and imaginary (reactive) components yields:

$$R(\omega) = R_{\infty} + \frac{(R_0 - R_{\infty}) \left[1 + (\omega\tau)^{\alpha} \cos\left(\frac{\alpha\pi}{2}\right) \right]}{1 + 2(\omega\tau)^{\alpha} \cos\left(\frac{\alpha\pi}{2}\right) + (\omega\tau)^{2\alpha}} \quad (3)$$

and

$$X_c(\omega) = -\frac{(R_0 - R_{\infty})(\omega\tau)^{\alpha} \sin\left(\frac{\alpha\pi}{2}\right)}{1 + 2(\omega\tau)^{\alpha} \cos\left(\frac{\alpha\pi}{2}\right) + (\omega\tau)^{2\alpha}} \quad (4)$$

where $j = \sqrt{-1}$ represents the imaginary unit, underpins the ability of BIA to discern physiological states [3,4]. Thus, the scalar impedance magnitude $|Z(\omega)|$ is subsequently derived as:

$$|Z(\omega)| = \sqrt{R(\omega)^2 + X_c(\omega)^2} \quad (5)$$

While extracted Cole parameters (R_0 , R_{∞} , τ , and α) provide valuable insight into underlying tissue biophysics, the diagnostic utility and numerical stability of any single parameter vary considerably depending on measurement geometry, frequency range, electrode-skin interface stability, and the specific fitting algorithm deployed. Instead of relying on full analytical expansions of real and imaginary impedance components, modern computational pipelines directly ingest complex spectral vectors $Z(\omega)$ or extracted Cole parameters ($R_0, R_{\infty}, \tau, \alpha$) to map non-linear pathological variations, bypassing the numerical instability of iterative non-linear curve fitting. The characteristic relaxation time τ encapsulates the intrinsic biophysical relaxation mechanics of the underlying cellular structure, reflecting the rate of interfacial polarization across cell membranes [38,41]. While τ demonstrates relative stability against minor electrode placement displacements in controlled experimental setups [41], its numerical stability and diagnostic reliability remain tightly coupled to the scanned frequency spectrum, measurement geometry, and the optimization routine employed [22,41]. Similarly, the dispersion exponent α quantifies multi-scale structural heterogeneity and non-ideal capacitive behavior [39,40], whereas R_0 and R_{∞} physically represent extracellular and total body water conduction boundaries, respectively [36,37]. Because isolated parameter fits are susceptible to localized noise and ill-conditioned optimization, modern computational pipelines evaluate multivariate parameter combinations rather than assuming single-parameter robustness [22,42].

2.2. Measurement techniques

A tetrapolar electrode configuration is employed in bioimpedance measurements to minimize skin-electrode contact artifacts and ensure precise data collection across clinical and research settings [43,44]. This setup usually has two current-injecting electrodes and two voltage-sensing electrodes. This mitigates the impact of skin impedance, thereby improving measurement accuracy [45,46]. Moreover, multiple BIA configurations have been developed for specialized applications. Single-frequency BIA (SF-BIA), conventionally performed at 50 kHz, offers a cost-effective approach for estimating fundamental body composition parameters, including fat mass (FM) and fat-free mass (FFM). Nevertheless, it is constrained by its inability to differentiate fluid compartments [47].

Multi-frequency BIA (MF-BIA) and BIS, which work across a range of 5 to 1000 kHz, give a more detailed picture of fluid balance and cellular health by measuring ECW and ICW dynamics [48,49].

EIT enhances this functionality by reconstructing two- or three-dimensional impedance distributions, thereby enabling applications such as lung ventilation monitoring or tumor localization via spatial conductivity mapping [50,51]. Empirical regression equations are widely employed to estimate body composition parameters, typically formulated as:

$$\text{FFM} = a \cdot \frac{H^2}{Z} + b \cdot W + c \cdot A + d \quad (6)$$

where a , b , c , and d are empirically derived coefficients [52], H is height, Z is impedance, W is weight, and A is age. These equations utilize the impedance index (H^2/Z) to consider body geometry; however, their estimation performance is constrained introducing substantial systematic bias and wide limits of agreement in populations with modified physiology, including the elderly, obese individuals, or those with chronic illnesses, due to their dependence on the assumptions of constant hydration and uniform tissue characteristics [22,53]. To improve diagnostic accuracy and clinical utility, advanced analytical frameworks are required to account for confounding physiological variables, such as postural fluid shifts and acute electrode repositioning [54]. The Schematic overview of BIA: (a) two- and four-electrode measurement methods in plants and humans with corresponding cellular analogs, (b) major body composition compartments relative to total body weight, (c) direct and alternating current pathways through skin tissue, and (d) workflow from portable impedance analyzers to AI, ML, and DL-based data analysis are illustrated in Figure 1.

2.3. Physical acquisition dynamics and confounding variables

While computational models optimize parameter estimation and pattern recognition downstream, their fidelity remains strictly bounded by the physics of data acquisition. In practice, bioimpedance measurements represent an intricate interplay of biophysical and environmental confounders that, if unmodeled, compromise signal integrity before algorithmic processing:

- **Electrode Interface and Contact Impedance:** Non-uniform contact pressure, skin hydration variations, and stratum corneum dielectric dispersion introduce high skin-electrode contact impedance. Tetrapolar configurations mitigate this effect, but dynamic skin-electrode impedance mismatches can generate baseline drift and phase distortions.
- **Physiological and Environmental Confounders:** Acute posture adjustments induce gravitational fluid shifts between intravascular and interstitial spaces, altering segmental resistance by up to 10–15%. Furthermore, ambient temperature fluctuations and localized perspiration alter cuticular electrolyte concentration, creating confounding conductive pathways.
- **Tissue Anisotropy and Geometry:** Biological tissues (such as skeletal muscle) exhibit direction-dependent electrical conductivity. Inconsistent electrode alignment relative to muscle fiber orientation introduces directional variability in measured resistance and phase angle.
- **Instrumentation and Bandwidth Limits:** High-frequency parasitic stray capacitances (typically above 500 kHz) and low-frequency electrode polarization artifacts (below 5 kHz) constrain the reliable operational bandwidth of analog front-ends. Inter-device variations in current source stability and phase-sensitive demodulation introduce systematic calibration offsets across commercial instruments.

AI algorithms can learn to compensate for structured noise patterns only when the underlying physical variance is adequately represented across training data. Machine learning cannot recover physiological information that is systematically masked, clipped, or corrupted during physical signal

acquisition.

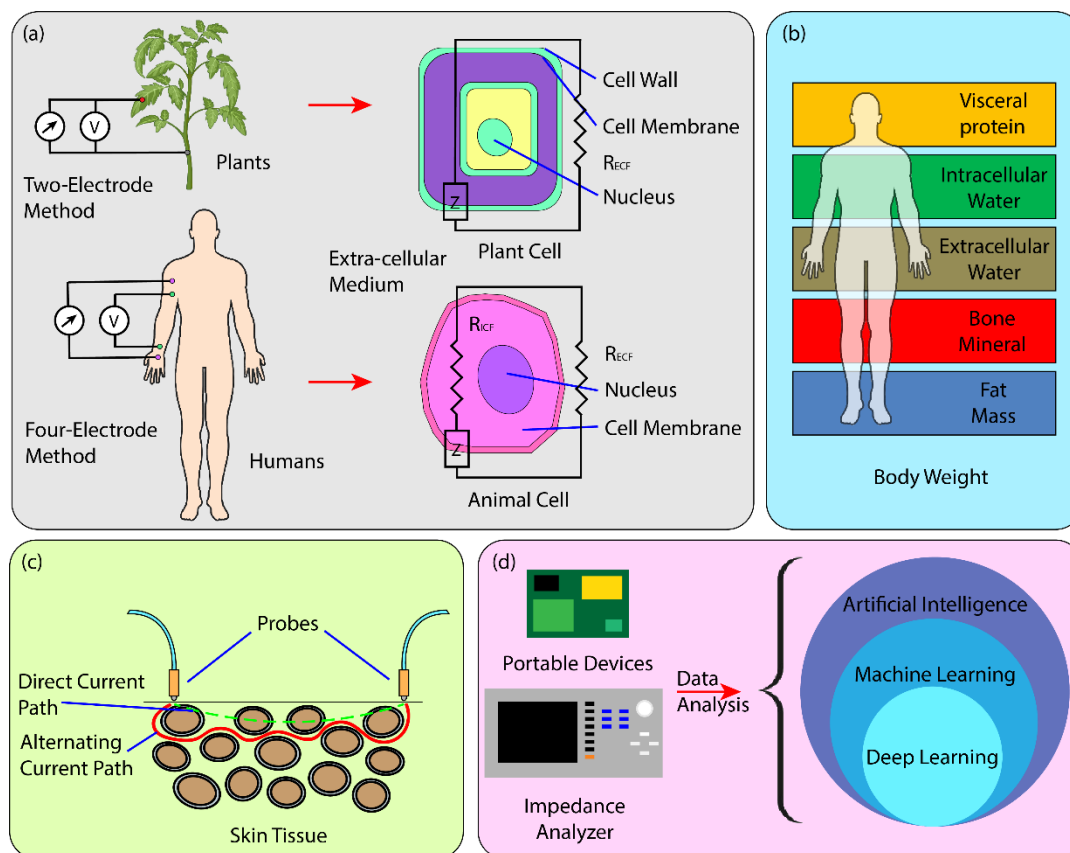


Figure 1. Measurement and analysis of Bioimpedance in (a) plants and humans and their corresponding cellular analog with two-electrode or four-electrode method. (b) The distribution of liquid and solid mass in the human body. (c) Bioimpedance measurement using direct and alternating current paths on skin tissue. (d) Bioimpedance data analysis of portable and benchtop devices using AI, ML, and DL.

2.4. Present status of bioimpedance in clinical settings

As a non-invasive, cost-effective alternative to classic isotopic dilution techniques, such as deuterium oxide dilution, BIA is utilized in clinical settings to evaluate human body composition, nutritional status, and fluid distribution boundaries [55]. By resolving lean tissue mass and adipose tissue mass independently, BIA metrics support targeted nutritional assessments in dialysis patients. This framework assists in identifying complex systemic risks, including sarcopenic obesity and protein-energy wasting, which frequently remain undetected by longitudinal body weight tracking alone [56]. In critical care settings, rigorous fluid tracking in postoperative patients is managed by monitoring the ECW ratio. In critical care settings, protocolized volume management guided by the extracellular water ratio (ECW/TBW) has been explored to direct post-resuscitation fluid de-escalation [57]. In a prospective, single-blind, randomized controlled trial conducted in a surgical intensive care unit, Chung et al. [57] evaluated BIA-guided fluid titration against traditional physician-directed care in a final analyzed cohort of 167 postoperative patients (intervention group:

n = 77; control group: n = 90). The trial's pre-specified primary endpoint was in-hospital mortality, which showed a non-significant reduction from 4.4% (4/90) in controls to 0% (0/77) in the intervention arm ($p = 0.125$). Among secondary endpoints, 28-day all-cause mortality demonstrated a significant reduction, dropping from 14.4% (13/90) under standard care to 1.3% (1/77) with BIA-guided diuretic and fluid titration ($p = 0.002$; adjusted OR = 9.90, 95% CI: 1.10–89.57). However, these findings must be interpreted with caution regarding broad translational readiness: The trial was conducted at a single academic center in a selected postoperative cohort (predominantly major abdominal surgery) with an unblinded clinical team and an imbalanced baseline malignancy rate between arms. Furthermore, prospective multicenter observational studies in broader intensive care cohorts such as that by Rochwerg et al. [58] across four Canadian ICUs (N = 159) demonstrated that while BIA vector length correlated with ongoing mechanical ventilation requirements, bioimpedance metrics exhibited wide empirical variability and did not associate with overall mortality in unselected sepsis. Consequently, multicenter randomized trials evaluating mortality as a pre-specified primary endpoint remain necessary before BIA-guided fluid protocols can be established as standard critical care practice. Furthermore, raw BIA metrics, most notably the phase angle, function as objective prognostic markers in oncological care. Depressed phase angle values correlate reliably with prolonged hospital stays and a high incidence of postoperative complications across malignancies, including colorectal, breast, and squamous cell head and neck carcinomas [59]. In patients with chronic kidney disease, multi-frequency tracking improves overall nutritional surveillance by facilitating fluid volume management and early malnutrition detection across both hemodialysis and peritoneal dialysis modalities [60].

Continuous physiological monitoring in dynamic environments is shifting from stationary, episodic instrumentation toward wearable, ambulatory bioimpedance configurations, including smartwatch arrays and patch-type sensors. Empirical validations demonstrate strong correlation coefficients ($r = 0.956$) between localized upper-limb bioimpedance increases and total-body dehydration-induced weight loss. These wearable arrays track acute fluid shifts in real time, detecting isotonic hypovolemia via localized extracellular resistance deviations of up to 13.6% following loop diuretic administration [61,62]. By stabilizing contact pressure boundaries, dual-channel wearable configurations capture arterial pulse waves to track changes in blood pressure and pulse wave velocity, providing continuous hemodynamic surveillance in cardiovascular care [63]. In respiratory tracking, thoracic bioimpedance patches maintain a linear relationship ($r > 0.965$) with tidal volume metrics under varying inspiratory loads, serving as a non-restrictive alternative for monitoring compromised breathing profiles [64]. This engineering transition toward flexible wearables establishes a shift from episodic, point-in-time laboratory testing to the integration of continuous bioimpedance data streams into daily clinical workflows, increasing accessibility for both inpatient and outpatient settings [55].

Emerging clinical applications of bioimpedance involve specialized diagnostics, including the management of secondary lymphedema and the tracking of neuromuscular degradation. BIVA and electrical impedance myography (EIM) serve as valuable tools for predictive outcome modeling. In post-surgical upper-limb lymphedema tracking, localized BIA reveals a significant correlation ($r = 0.599$) between shifts in the FFM ratio and quantitative reductions in excess limb volume. This relationship supports continuous tracking without requiring manual water-displacement volumetry [65]. Similarly, EIM and spatial EIT locate localized muscle atrophy, edematous fluid collections, and neoplastic tissue changes. In these workflows, EIT maps dynamic pulmonary ventilation distribution while EIM quantifies structural cell changes to grade the severity of neuromuscular disease progressions [66,67]. Under high-altitude environmental stress, BIVA monitors

circadian hydration dynamics, correlating absolute vector length directly with TBW fluctuations ($r^2 = 0.84$) and identifying the intracellular-to-extracellular fluid shifts associated with acute mountain sickness [68].

However, the clinical integration of BIA contains significant mathematical and physiological limitations that prevent its use as an isolated diagnostic system. In high-acuity septic shock patients in the intensive care unit, BIA tracking reveals a positive association between cumulative fluid retention and TBW metrics. Yet, the estimation fidelity of these volume equations is regularly degraded by systemic capillary leaks, altered membrane permeabilities, and peripheral tissue edema, resulting in substantial estimation error and wider limits of agreement [69,70]. Prospective multicenter clinical trials demonstrate no statistically significant correlation between raw BIVA vector lengths and mechanical ventilation duration or absolute survival outcomes in post-resuscitation sepsis cohorts. Wide limits of agreement in these studies highlight substantial random error and empirical noise, rendering BIA mathematically inadequate for exclusive use in high-stakes clinical treatment decisions [58]. Furthermore, while modern cellular relaxation models simplify cell health screening by analyzing frequency-dependent dielectric responses, these methods are highly sensitive to skin temperature fluctuations, sweat-induced electrolyte changes, and minor electrode displacement [71]. Consequently, while contemporary bioimpedance techniques show high technical sophistication, prospective, large-scale multi-center clinical trials remain an essential requirement to standardize data acquisition protocols and validate algorithms across demographically diverse human populations [54].

3. AI methodologies in bioimpedance analysis

By improving accuracy, automating data processing, and enabling predictive capabilities that go beyond the constraints of conventional methods, the incorporation of AI into BIA has substantially expanded its analytical framework [30]. ML, DL, generative models, and multimodal data fusion are examples of AI approaches that tackle issues such as noise, non-linearity, and data scarcity, increasing the applicability of BIA in a variety of clinical domains [17].

3.1. Machine learning for parameter estimation and artifact removal

To overcome the sensitivity of traditional gradient-based non-linear least squares algorithms to initial parameter initialization and measurement noise, non-gradient stochastic metaheuristic frameworks have been deployed for Cole parameter extraction [42]. In particular, Gholami-Boroujeny and Bolic demonstrated that bio-inspired optimization algorithms, specifically the Bacterial Foraging Optimization (BFO) algorithm, alongside Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), substantially improve the extraction of Cole parameters ($R_0, R_\infty, f_c, \alpha$) from multi-frequency bioimpedance spectra (1 kHz to 1 MHz). When tested across simulated datasets with random radial noise up to $\pm 30\%$, the BFO method maintained high parameter estimation fidelity, yielding mean absolute percentage errors below 0.65% across all Cole parameters (0.08% for R_0 , 0.32% for R_∞ , 0.29% for α , and 0.62% for f_c) [42]. In contrast, deterministic least-squares fitting degraded significantly under equivalent noise conditions, with parameter errors escalating up to 5.75% [42]. While stochastic metaheuristic search incurs higher execution latency (25.4 s for BFO versus 0.78 s for least squares), it circumvents premature convergence to local minima, yielding feature sets that enhance downstream classifier performance across anatomical postures [42]. In parallel, supervised

machine learning regressors have been explored to approximate non-linear impedance loci in quasi-real-time once trained, bypassing iterative fitting loops altogether.

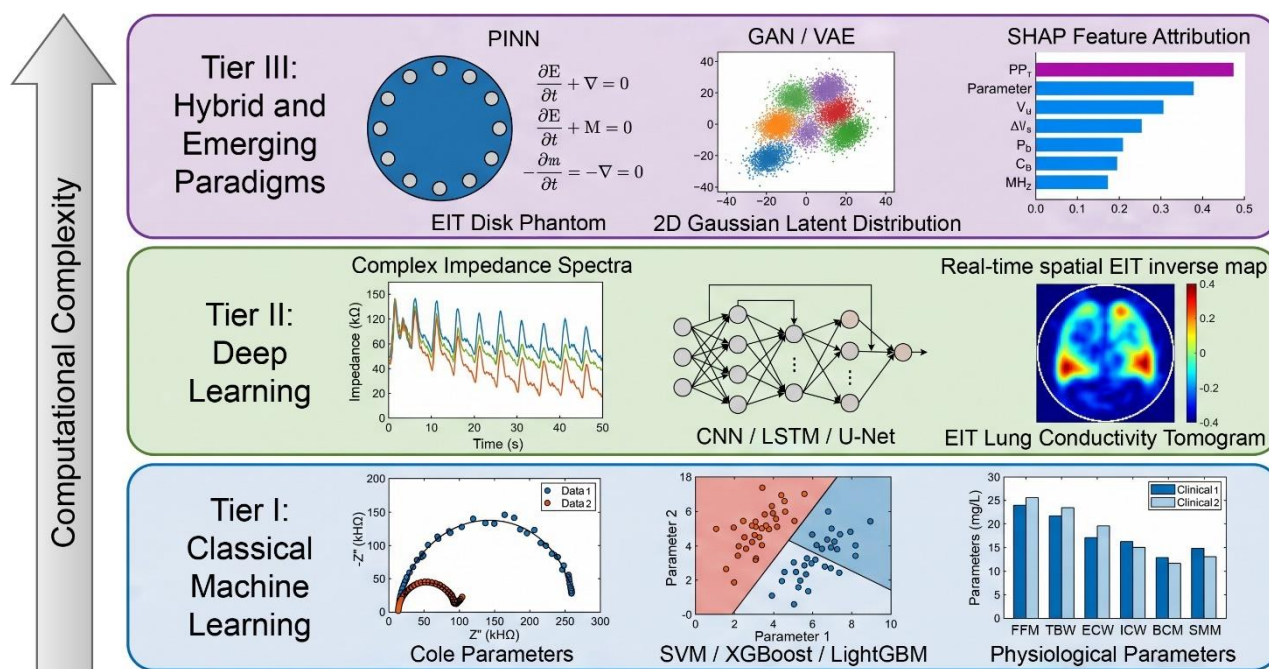


Figure 2. Hierarchical computational taxonomy mapping the transition from classical shallow machine learning (parameter extraction, linear classifiers) to deep representation architectures (CNNs, LSTMs, U-Net EIT reconstruction) to PINNs and generative data augmentation (GANs/VAEs), indicating increasing computational complexity.

Beyond passive parameter derivation, supervised ML architectures provide automated, real-time data post-processing across several clinical and cellular frameworks. By using electrical impedance spectroscopy data gathered from three distinct stem cell lines, multi-class ML frameworks successfully differentiate active cell proliferation and progressive cellular differentiation stages, creating a non-invasive, automated evaluation tool for regenerative medicine workflows [72]. Similarly, SVM classifiers demonstrate high discriminatory performance when separating healthy tissue impedance signals from pathological structural alterations induced by localized edema or neoplastic transformations, achieving high classification accuracy and balanced sensitivity-specificity profiles [18].

To translate these advanced processing capabilities into dedicated clinical hardware, Kalvøy et al. implemented real-time bioimpedance classification using needle-mounted sensor arrays to detect tissue boundaries and needle-to-nerve contact [73]. For continuous ambulatory deployment, modern low-power front-end architectures utilize auto-calibration loops and duty-cycled readouts to support continuous physiological monitoring in wearable devices [35].

Classical single-frequency and segmental BIA techniques evaluate whole-body or regional fluid distribution and tissue mass by resolving scalar resistance and reactance components. In these applications, AI operates primarily as a non-linear regression and classification tool to predict clinical outcomes (such as sarcopenia, malnutrition, or acute dehydration) and calculate body compartments (FFM, TBW). By learning complex multi-covariate interactions between impedance indices (H^2/Z), anthropometry, and clinical covariates, machine learning frameworks (e.g., Random Forests, Gradient

Boosting) overcome the rigid assumptions of constant 73% hydration inherent to classical linear empirical equations [52,74,75].

In addition to clinical diagnostics, non-human bioelectrical applications, such as plant pathology monitoring under environmental stress [76–79], potato dry-matter characterization [80], fish metabolic stress testing [81,82], and Atlantic salmon supply-chain traceability systems [83,84] serve as valuable experimental testbeds. While biological variability and regulatory thresholds differ substantially from human healthcare, these parallel domains share foundational mathematical principles in Cole parameter fitting and sensor fusion.

To address data scarcity in specialized patient cohorts, transfer learning architectures represent a potential domain-adaptation strategy. By leveraging networks pre-trained on larger baseline datasets, transfer learning facilitates weight adaptation to targeted single-center cohorts with smaller sample sizes, mitigating overfitting risks. Nonetheless, whether domain-adapted representations maintain consistent performance across demographically diverse populations remains an open question requiring multi-center external validation [85]. The hierarchical computational taxonomy maps the transition across three progressive tiers of AI-driven bioimpedance analysis: Advancing from Tier I classical machine learning algorithms (SVM, XGBoost, LightGBM) for Cole parameter estimation and clinical stratification, to Tier II deep representation networks (CNNs, LSTMs, U-Net) for continuous temporal tracking and dynamic spatial EIT tomogram reconstruction, and ultimately to Tier III hybrid paradigms integrating physics-informed neural networks (PINNs), generative digital phantom augmentation (GAN/VAE), and game-theoretic interpretability audits (SHAP) is shown in Figure 2.

3.2. Deep learning for spectral and image analysis

DL architectures, specifically CNNs and U-Net variants, significantly alter the processing of multi-frequency bioimpedance spectra and the spatial reconstruction of EIT images. The spatial mapping of internal tissue conductivity via EIT requires resolving an inverse mathematical problem that is inherently non-linear and ill-posed. Minor measurement noises at the boundary electrodes can produce extreme geometric artifacts when using classical reconstruction models, such as Tikhonov regularization or one-step Newton-Raphson methods.

To mitigate these boundary vulnerabilities, deep neural network layers bypass standard iterative matrix inversions by directly learning the non-linear mappings between raw boundary voltage vectors and internal cross-sectional conductivity distributions. Empirically, optimized CNN and U-Net frameworks improve structural image resolution relative to standard Tikhonov routines. This computational optimization enables the high-fidelity spatial visualization of dynamic regional conductivity, a capability critical for point-of-care clinical tracking modalities such as real-time lung ventilation monitoring and the localization of alveolar over-distension or collapse [86].

For BIS data arrays, deep convolutional architectures convert continuous frequency-dependent impedance signatures into two-dimensional topological feature maps across separate resistance and reactance axes. By extracting localized, non-linear multi-frequency relationships, these networks identify distinct tissue properties, significantly increasing the accuracy of pathological tissue classification [87].

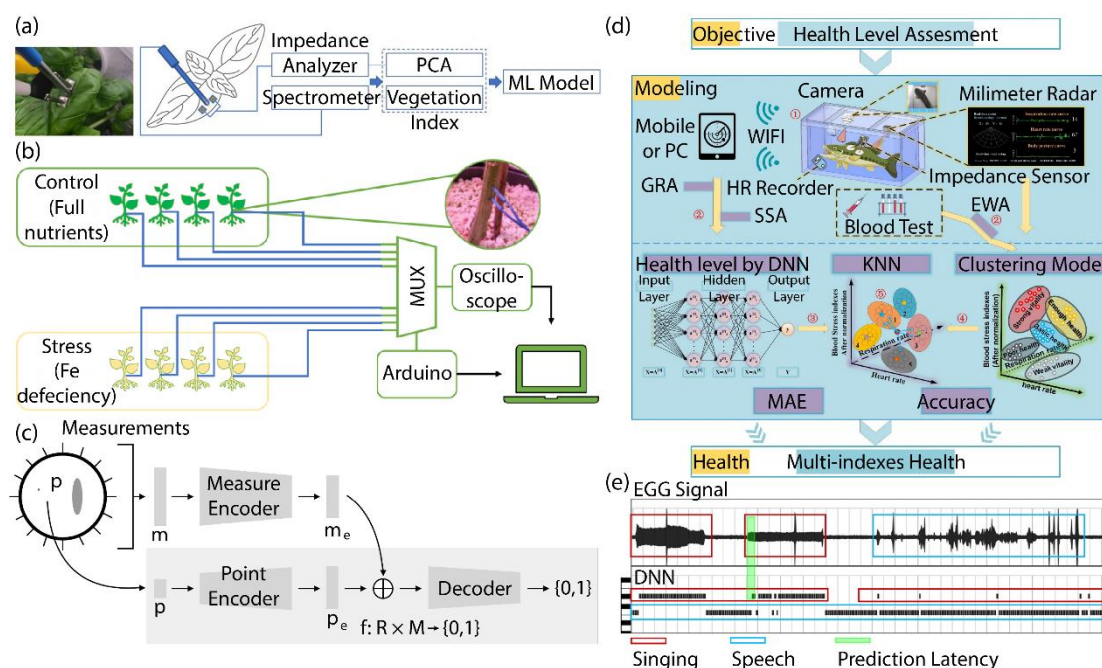


Figure 3. (a) Overview of bioimpedance and optical measurements in sweet basil, with ML model construction for classification [77]. Reproduced with permission from Elsevier. (b) Bioimpedance was monitored in both plant groups using Analog Discovery 2, multiplexed via an Arduino-controlled Python script [76]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (c) Schematic of implicit EIT architecture where measurement and point encoders fuse to predict anomaly probability via decoder [86]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (d) A multi-sensor system using bioimpedance, camera, and radar to monitor fish health during transport, integrating DL models such as GRU/CNN-LSTM and clustering for real-time multi-level health assessment [84]. Reproduced with permission from Elsevier. (e) Bioimpedance-based DL classifies speaking/singing voices with real-time audio-MIDI evaluation [88]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY).

Extending these analytical layers to advanced human physiological signal discrimination, Donati et al. implemented a real-time DL classifier that utilizes localized laryngeal bioimpedance data to separate speaking from singing voices. This system achieves an overall testing classification accuracy between 92% and 94% (reaching approximately 92% on unseen samples and 94% during validation) with low computational overhead, demonstrating the technical feasibility of bioimpedance-based vocal tracking and voice-to-MIDI conversion [88].

Beyond human clinical contexts, deep learning frameworks have demonstrated significant utility in parallel bioelectrical applications, including plant physiology monitoring and aquatic biomass assessment [76–84]. Although biological variability and regulatory thresholds differ markedly between agricultural systems and clinical healthcare, these foundational models provide valuable methodological benchmarks for non-linear feature extraction and multi-sensor data alignment. Figure 3 shows the applications of bioimpedance spectroscopy integrated with machine learning and deep learning: (a, b) non-invasive stress detection in plants using impedance measurements and ML

classification, (c) implicit EIT architecture for anomaly detection, (d) multi-modal system combining bioimpedance, camera, and radar sensors with deep learning models for real-time fish health assessment during waterless transport, and (e) bioimpedance-based deep learning for real-time classification of speaking versus singing voices with MIDI conversion.

Multi-frequency bioimpedance analysis and bioimpedance spectroscopy record frequency-dependent dispersion profiles governed by cellular relaxation mechanics. Here, the analytical objective shifts from scalar estimation to parameter extraction (e.g., Cole model parameters R_0 , R_∞ , τ , α) and multi-frequency pattern recognition. Supervised machine learning algorithms (such as SVMs and MLPs) bypass computationally expensive, iterative non-linear curve fitting by mapping continuous impedance spectra directly to underlying tissue states, enabling automated classification of pathological tissue alterations, cell proliferation stages, and cellular membrane integrity [18,42,72]. Collectively, these DL methodologies handle high-dimensional, non-linear, and time-varying data structures far more effectively than classical linear statistical equations. This structural shift provides a significant advancement in diagnostic precision and forms a robust computational baseline for real-time, non-invasive patient tracking.

3.3. Generative models for data augmentation

The paucity of large-scale, annotated BIA datasets frequently comprising fewer than 1,000 samples represents a significant barrier to the development of robust DL models. Generative architectures, such as VAEs and GANs, mitigate this bottleneck by synthesizing impedance spectra that augment dataset volume by 10–20 times while maintaining statistical fidelity [89,90]. These augmented datasets facilitate the optimization of complex DL models in scenarios with limited clinical data, such as the diagnosis of cholelithiasis [91], the assessment of knee arthritis severity [92,93], and the detection of obstructive sleep apnea [94]. Furthermore, score-based diffusion models have emerged as a novel methodology for creating higher spatial resolution digital phantoms. These phantoms provide a rigorous framework for EIT validation, reducing the reliance on costly and ethically complex in-vivo studies [95].

Complementing these computational advances, wearable bioimpedance devices have been coupled with machine learning to track dynamic metabolic and behavioral biomarkers. For example, Sanai et al. evaluated a wearable ring bioimpedance spectroscopy prototype paired with gradient boosted decision trees for non-invasive continuous glucose monitoring, achieving a Mean Absolute Relative Difference (MARD) of 17.9% against reference continuous glucose sensor data in individuals with type 2 diabetes [27]. Similarly, Liu et al. demonstrated the utility of dynamic wrist-to-wrist bioimpedance transients for automatic dietary monitoring (the *iEat* system), leveraging closed-loop circuit alterations during dining to classify food intake activities and food categories via lightweight sequence models [28]. By establishing robust pipelines to extract physiological and behavioral metrics under ambulatory conditions, these architectures illustrate the expanding scope of AI-driven bioimpedance beyond classical static body composition. The applications of GANs and ML in BIA: (a) distribution of GAN architectures and clinical applications in healthcare, (b) electrode placement on the knee for dynamic bioimpedance measurements during extension, flexion, standing, and gait, (c) comparative accuracy of various ML models, and (d) experimental hardware setup with confusion matrix for multi-class classification are shown in Figure 4.

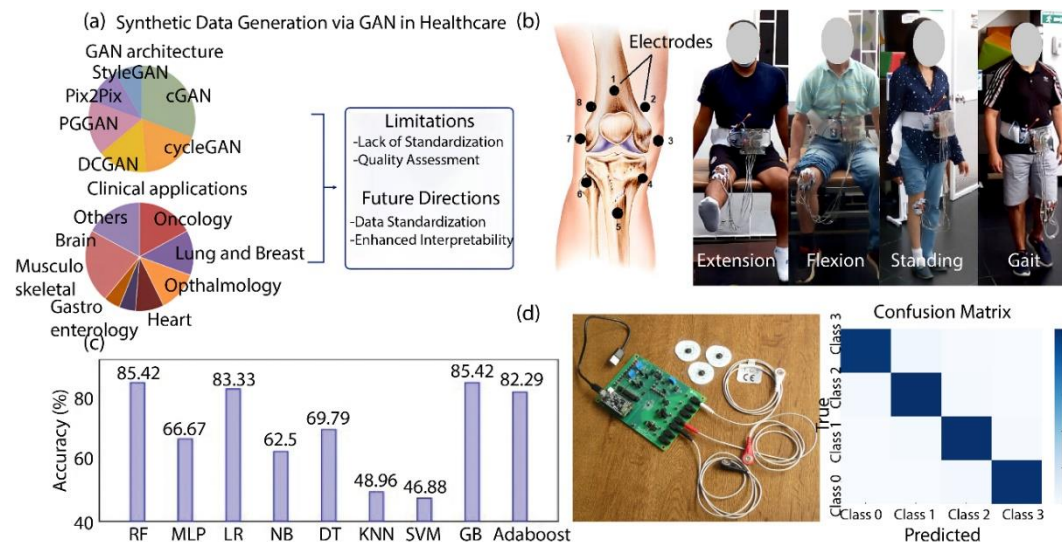


Figure 4. (a) The use of GAN architecture to generate synthetic data in healthcare [89]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (b) Knee osteoarthritis diagnosis using bioimpedance electrode setup in dynamic poses [93]. Reproduced with permission from IOP Publishing. (c) The comparison of ML models in bioimpedance measurement for the prediction of gallstone disease [91]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (d) Experimental hardware setup and confusion matrix of the LightGBM classifier distinguishing four physiological and movement conditions (normal breathing, breath-holding, walking, and physical effort) in a single-subject study combining wearable ECG and multi-frequency bioimpedance [96]. Reproduced with permission from Elsevier.

3.4. Multimodal data fusion

The analytical capacity of AI to integrate multi-frequency bioimpedance arrays with complementary physiological data streams such as ECG, heart rate variability (HRV), and tri-axial accelerometry supports a shift toward comprehensive, contextualized patient health modeling. Traditional bioimpedance monitoring configurations process electrical tissue data in isolation, leaving the computational downstream vulnerable to motion artifacts and static demographic baseline errors.

To overcome these isolated processing limits, multimodal data fusion structures treat bioimpedance signals as an added descriptive dimension within a broader physiological network. For example, Jain et al. explored multi-sensor gating by combining multi-frequency electrical bioimpedance (125 Hz to 128 kHz) and single-lead ECG collected via a MAX30001 analog front-end within a LightGBM gradient boosting classifier. Rather than evaluating a clinical patient cohort, their experimental protocol was conducted on a single healthy volunteer ($N = 1$) performing four distinct physiological and movement conditions (normal breathing, breath-holding, walking, and post-squat physical exertion). The model achieved a test accuracy of 94.49% (with 5-fold cross-validation of 95.86% and class F1-scores exceeding 0.95) for discriminating these activity and respiratory states. While this demonstrates the technical feasibility of synchronized multimodal data acquisition for wearable motion and activity gating, its utility for cardiovascular disease diagnosis remains an exploratory premise that requires clinical validation in patient cohorts [96].

Furthermore, multimodal fusion frameworks improve tissue classification performance by pairing electrical impedance spectra with localized mechanical elasticity signatures, enhancing sensitivity and specificity in discriminating benign from malignant margins. To support real-time tissue hydration monitoring and pathological tissue characterization, Ege et al. developed a low-power bioimpedance measurement platform integrated with a multimodal ML classifier. Their architecture combines localized mechanical tissue stiffness, contact pressure metrics, and electrical impedance spectroscopy signatures gathered from healthy and malignant urinary bladder structures [97]. By pairing mechanical elastic deformations with frequency-dependent electrical conductance vectors, this multi-modal sensor fusion model differentiates benign tissue boundaries from malignant cellular mutations more effectively than standalone impedance metrics, providing a predictable tool for intraoperative tissue characterization.

Beyond real-time macro-level physiological tracking, advanced ensemble learning algorithms scale this data fusion models to include micro-level, cross-domain structures by intersecting BIS with patient genomic profile matrices. By blending raw cellular dielectric relaxation parameters with specific genetic variants and high-dimensional demographic vectors, integrated ensemble models eliminate the baseline structural errors inherent to empirical population equations. Preliminary investigations suggest that integrating multi-frequency spectra with complementary physiological and demographic features can improve personalized fat-free mass estimation over conventional single-frequency baseline equations [55,98]. However, these performance increments remain bounded by the cohort dimensions and validation splits employed.

This multimodal data fusion strategy combining localized mechanical elasticity, contact pressure indices, and multi-frequency impedance profiles illustrates a feasible engineering framework for integrating complementary sensor streams. However, transitioning from exploratory multi-sensor prototypes to reliable clinical monitoring requires rigorous external validation across heterogeneous cohorts to establish reproducibility beyond controlled benchtop environments [98].

4. Applications of AI in bioimpedance

4.1. Body composition and nutritional assessment

Human body composition metrics, including absolute FM, FFM, body mass index (BMI), and appendicular lean mass, serve as foundational diagnostic pillars for objective nutritional surveillance and physiological performance optimization. The deployment of AI frameworks within BIA addresses long-standing estimation bias and limits-of-agreement constraints inherent to commercial hardware readouts [99,100]. Methodologically, Franco-Villoria et al. exposed systematic vulnerabilities in black-box hardware configurations, demonstrating that commercial device equations rely predominantly on body weight rather than measured electrical impedance, which introduces substantial size-dependent bias and wide limits of agreement [101]. In clinical geriatrics, Random Forest models identified hidden sarcopenia and protein-energy malnutrition validated against the Asian Working Group for Sarcopenia (AWGS) criteria, which combine appendicular lean mass with grip strength measurements [74,75]. This distinction highlights a clear rationale for advanced computational modeling: Traditional empirical regression lines degrade when processing biological variability, whereas ML and DL architectures bypass rigid linear constraints by treating raw multi-frequency spectrum arrays as high-dimensional non-linear feature maps. To guide the structural mapping of the literature within this paper, Table 1 outlines the chronological evolution and development of bioimpedance technologies integrated with various AI models.

Table 1. Methodological taxonomy and technological advancements in AI-integrated bioimpedance.

Methodology	Target Task	Dataset	Computational Methodology or AI	Evaluation Metric	Reported Value	Numerical	Validation Context	Reference
Foundational Biophysical Modeling	Whole-body FFM and TBW estimation via single-frequency tetrapolar BIA (50 kHz)	37 healthy adult males (age: 28.8 ± 7.1 y)	Linear regression using stature-impedance index	Pearson correlation (r)	Accuracy = NR, Sensitivity = NR, Specificity = NR, FFM having water content 72–74%, Reliability: $r = 0.99$ (5-day CV = 2.0%)		Internal cohort fit (no holdout/CV); reference methods: hydrodensitometry (FFM) and D ₂ O dilution (TBW)	[52]
Clinical Vector Analysis (BIVA)	Semi-quantitative fluid overload & apparent edema detection via 50 kHz tetrapolar $R-X_c$ graph	217 Caucasian adults: 86 healthy controls, 91 renal disease patients (29 with apparent edema), 40 obese	Bivariate normal distribution of height-scaled vectors (R/H, X_c/H) generating 75% & 95% tolerance ellipses	Sensitivity (edema detection) and healthy control false-positive rate at the lower pole threshold	Accuracy = NR, Sensitivity: 97% (28/29 apparent edema cases fall outside the 75% lower pole), Specificity = NR		Single-center observational cohort; clinically observed peripheral edema serves as comparator; qualitative vector thresholding without iterative CV	[102]
Supervised Machine Learning	3-class discrimination of fresh, frozen-thawed, and freeze-thaw cycled salmon fillets via two-frequency BIA (1 kHz & 16 kHz)	720 Atlantic salmon (Salmo salar) fillet samples (240 fresh, 240 frozen-thawed, 240 freeze-thaw cycles)	Support vector machine (SVM), linear discriminant analysis (LDA), K-nearest neighbors (KNN), and random forest (RF)	Classification Accuracy, Precision, Recall, and F_1 score (10% test holdout, $n = 71$ samples)	Accuracy = 98%, Precision = 97%, Recall = 97%, F_1 score = 97%, Specificity = NR in quality evaluation and frozen-thawed state discrimination		90/10 train/test split on laboratory food samples; bench-top non-destructive testing; food quality evaluation (non-clinical)	[83]

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Methodology	Target Task	Dataset	Computational Methodology or AI	Evaluation Metric	Reported Numerical Value	Validation Context	Reference
Supervised Learning & Multimodal Physiological Fusion	Binary detection of acute lung fluid accumulation via transthoracic bioimpedance (10–999 kHz) fused with ECG-derived HRV	60 hospitalized participants: 28 ADHF patients (23 baseline with fluid, 17 discharge) and 32 matched controls (72 usable recordings)	Cubic Support Vector Machine (Cubic SVM) trained on 6 features: 3 TBI (R_0, R_I, C_m) + 3 HRV (LF, PDMI parasympathetic, mean HR)	Classification Accuracy, Sensitivity, and Specificity evaluated via leave-one-subject-out cross-validation (LOSO-CV)	Accuracy = 92% (vs. 82% for TBI alone, 75% for HRV alone), Sensitivity = 82.6% (19/23 fluid-overload baseline cases), Specificity = 95.9% (47/49 non-fluid control/discharge cases)	Single-center prospective clinical study; LOSO-CV across 60 subjects; clinical admission/discharge status serves as diagnostic ground truth	[103]
Deep Learning	2D conductivity boundary and shape reconstruction from 16-electrode EIT differential voltage measurements	42,830 simulation samples (85% train, 15% test) + 4 physical saline tank phantoms with insulating glass rod inclusions	Dual-Branch U-Net (DHU-Net): DCN-SE branch for shape extraction, CA-HyperConv branch for conductivity mapping	Root Mean Square Error (RMSE), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR)	Accuracy = NR, Test Simulation: RMSE = 2.0637, SSIM = 0.9522, PSNR = 46.46 dB (68.8% RMSE reduction vs. Tikhonov regularization), Sensitivity = NR, Specificity = NR; Inference Latency: 3.30 s per 128×128 image	Numerical FEM simulations and experimental bench-top saline tank validation; non-biological engineering verification	[104]

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Methodology	Target Task	Dataset	Computational Methodology or AI	Evaluation Metric	Reported Numerical Value	Validation Context	Reference
Embedded Edge AI	Real-time skin-electrode adhesion gating & detached-electrode identification via 4-wire BIS (1–100 kHz)	Real-time skin-electrode adhesion gating & detached-electrode identification via 4-wire BIS (1–100 kHz)	Cascaded embedded MLPs (MLP1: 200–100–1; MLP2: 200–100–50–25–4) deployed on ARM Cortex-M4 (STM32F401RE)	Classification Accuracy, F_1 -score, AUC, on-chip latency, and MCU memory footprint	Stage 1: Accuracy = 98% ± 3% ($F1 = 0.98$); Stage 2: Accuracy = 97% ± 13% ($F1 = 0.97$); Sensitivity = NR, Specificity = NR, MCU latency: 4.29 ms; footprint: 13% Flash, 41% RAM	Subject-wise LOSO-CV across 31 subjects; on-device MCU deployment	[105]
Generative AI	2D electrical conductivity image reconstruction and data augmentation from boundary voltages in EIT	Synthetic geometric phantoms (233,280 augmented simulation images; 10,000 unseen test images evaluated across Inf to 20 dB SNR)	Variational Neural Network Reconstruction (VNNR): VAE-based data augmentation paired with an 11-layer MLP voltage-to-latent mapper and VAE decoder	Structural Similarity Index (SSIM) and Normalized Mean Squared Error (NMSE) across varying Gaussian noise levels	Accuracy = NR, Sensitivity = NR, Specificity = NR, SSIM = 99.23%, NMES = 4.29% under noise-added EIT reconstruction	10,000 synthetic test phantoms generated via EIDORS simulation; non-biological, numerical engineering benchmarking (no physical tank or clinical testing)	[90]
Physics-Informed Deep Learning	Non-linear conductivity mapping & structural damage localization via DC boundary potential EIT	Physical specimens: 16-electrode carbon-fiber truss and 20-electrode NACA 4424 airfoil; 50,000 synthetic FEM forward models	3-branch PINN predicting binary conductivity σ_p (BCE loss), boundary potentials V_p (L_1 loss), and internal potentials u_p (L_1 loss)	Qualitative reconstruction artifact suppression, localized damage fidelity, and computational inference speedup	Accuracy = NR, Sensitivity = NR, Specificity = NR, Matches classical NLDI fidelity with $\sim 80,000 \times$ faster inference	10,000 synthetic FEM validation holdouts + physical carbon-fiber specimen testing; structural non-destructive evaluation (non-biological)	[106]

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Methodology	Target Task	Dataset	Computational Methodology or AI	Evaluation Metric	Reported Numerical Value	Validation Context	Reference
Multimodal Physiological Fusion & Gradient Boosting	4-class discrimination of physiological/motion states (breathing, breath-holding, squats, walking) via wearable ECG & 11-frequency BioZ (125 Hz–128 kHz)	Single healthy male subject (N = 1, 27 y); 88 synchronized signal records (44 ECG, 44 BioZ) totaling ≈ 45 min	Light Gradient Boosting Machine (LightGBM) with leaf-wise tree growth (tuned with 100 leaves, learning rate 0.1, 300 estimators)	Classification Accuracy, Precision, Recall, F1-score, 5-/10-fold Cross-Validation (CV), and ROC AUC	Accuracy = 94.49% (5-fold CV = 95.86%, 10-fold CV = 96.16%), Sensitivity = NR, Specificity = NR	Single-subject exploratory proof-of-concept (N = 1); k-fold CV on short-duration continuous time series; laboratory motion gating (non-clinical cohort)	[96]
Explainable AI	Acute post-exercise dehydration estimation and fluid loss detection via segmental multi-frequency BIA (1 kHz–1 MHz)	43 healthy young adults (36 M / 7 F; age 24.40 ± 6.47 y); 143 post-exercise measurement sessions	Gradient Boosting Regression Trees (GBRT) + multivariate linear regression with SHAP feature explanations	Continuous coefficient of determination (R^2), ROC AUC, Sensitivity, and Specificity	Accuracy = NR, Dehydration prediction $R^2 = 0.55$; SHAP attribution with AUC = 0.876 for > 2% fluid loss, Sensitivity = NR, Specificity = NR	5-fold cross-validation on training data with held-out test evaluation; comparator: pre- vs. post-exercise scale body weight change (no external cohort)	[107]

(NR = not reported)

To achieve parity with clinical reference standards without relying on ionizing radiation, modern translational frameworks have paired bioelectrical impedance with non-invasive optical surface anthropometry. Rather than utilizing deep neural networks, Bennett et al. established a rapid five-compartment (3DO-5C) molecular model that couples multi-frequency BIA with 3-dimensional optical (3DO) surface scanning [108]. By using calibrated linear regression to substitute 3DO body volume for air displacement plethysmography and BIA total body water for deuterium oxide dilution, their framework demonstrated near-perfect concordance with criterion multicompartments models (concordance correlation coefficient = 0.99 for fat-free mass, RMSE = 1.75 kg) without requiring iterative neural architectures [108]. In parallel, deep learning has been deployed in standalone optical anthropometry to automate complex geometric feature extraction; for instance, Tian et al. implemented a 3D graph convolutional autoencoder paired with Gaussian process regression to map irregular 3D surface meshes directly to FFM indices, outperforming classical linear

principal component analysis and providing a scalable alternative to longitudinal dual-energy X-ray absorptiometry (DXA) scanning [109].

In clinical geriatrics and nutritional research, RF classifiers exhibit high diagnostic sensitivity when optimizing screening protocols for muscle-wasting disorders. By ingesting raw phase angle values and the geometric impedance index (height squared divided by impedance), optimized RF models detect protein-energy malnutrition and hidden sarcopenia in frail, older populations, providing an objective, non-invasive triage alternative to manual anthropometric measurements [74]. Parallel advancements in athletic training utilize segmental MF-BIA combined with supervised ML to monitor dynamic fluid shifts during intense physical exertion. By demonstrating significant linear correlation ($r > 0.85$) between active impedance vector trajectories and peak metabolic performance markers (such as peak oxygen consumption, VO_2 peak), these models support the formulation of individualized hydration protocols in sports medicine. However, linear correlation alone does not confirm clinical interchangeability, which requires formal agreement analysis (Bland–Altman bias and limits of agreement) against reference physiological standards [107,110].

To improve clinical interpretability and model transparency in high-capacity deep networks, XAI layers and human-machine interfaces (HMIs) have been integrated into body composition workflows. Figure 5 illustrates representative implementations across feature attribution, physics-informed regularization, and agreement validation. Panel (a) presents SHAP summary plots, which estimate model-based feature attributions to illustrate how individual multi-frequency impedance variables and demographic covariates mathematically contribute to the algorithm's predictions of fat mass index (FMI) and fat-free mass index (FFMI), without implying direct biological causality. Panel (b) details the configuration of a three-tiered Physics-Informed Neural Network used for spatial conductivity mapping, where underlying Maxwell's volume equations are embedded directly into the network's loss function to regularize backpropagation paths. Panel (c) provides standardized Bland–Altman plots evaluating inter-method agreement (mean systematic bias and 95% limits of agreement) rather than linear correlation between multi-frequency BIA measurements and criterion DXA values for fat mass index (FMI), fat-free mass index (FFMI), and body mass index (BMI). Methodologically, Bland–Altman analysis must not be conflated with linear correlation: While Pearson's r merely evaluates the strength of a linear association between two methods, it remains insensitive to systematic calibration offsets or scale errors. In contrast, Bland–Altman analysis establishes whether two measurement modalities can be used interchangeably by quantifying the mean difference (systematic bias, $\bar{d}$) and the 95% limits of agreement ($\bar{d} \pm 1.96 \times \text{SD}$), while revealing potential proportional bias across the measurement range. Panels (d) depict non-invasive wearable electrode configurations deployed for continuous real-time physiological tracking. To ensure stable performance in niche or data-sparse patient cohorts, these deep architectures utilize transfer learning configurations, enabling a network pre-trained on comprehensive consumer datasets to adapt effectively to specialized clinical targets. This intersection of advanced computing and bioelectrical measurement moves BIA beyond static regression baselines, offering potential pathways toward more scalable and personalized nutritional assessment.

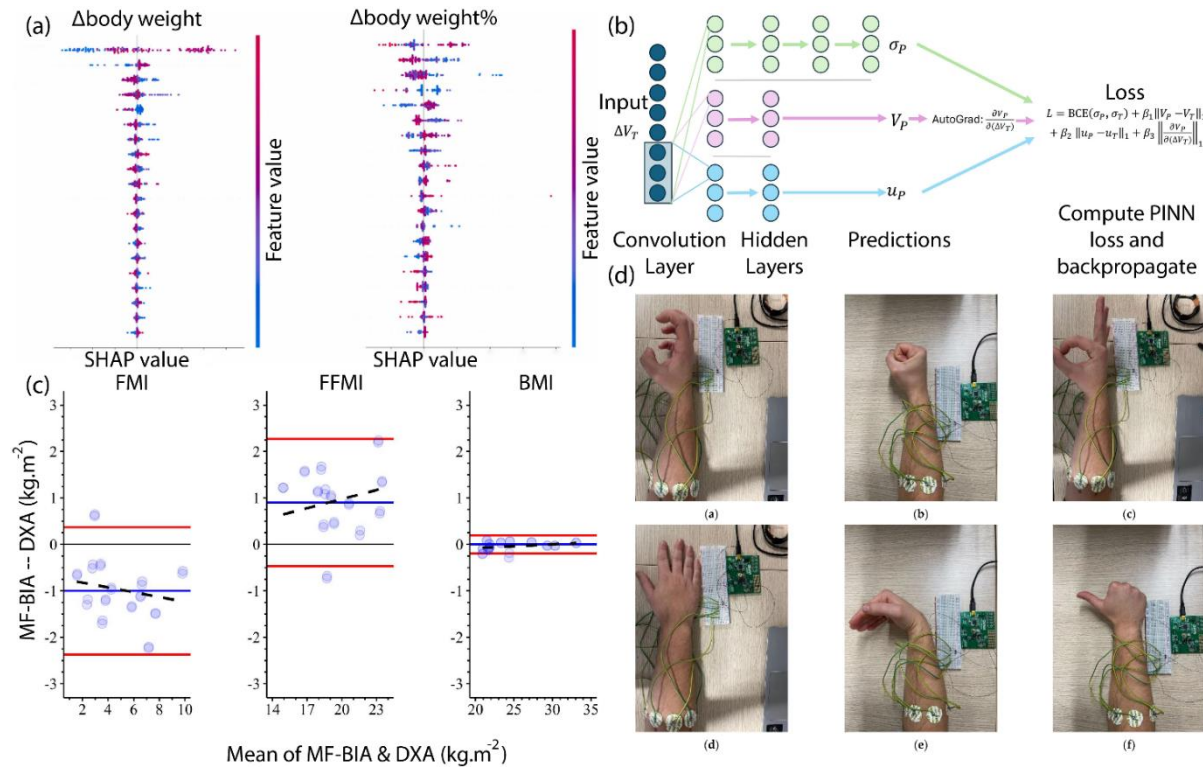


Figure 5. (a) Segmental MF-BIA features are ranked using Shapley Additive Explanations analysis to predict post-exercise dehydration [107]. Reproduced with permission from KeAi Publishing. (b) Mixed classification-regression in EIT reconstruction using a three-tiered PINN architecture [106]. Reproduced with permission from Elsevier. (c) Bland–Altman analysis assessing inter-method agreement quantified via mean systematic bias (blue solid line) and 95% limits of agreement (red solid lines, mean $\pm$ 1.96 SD) rather than linear correlation between MF-BIA and DXA for FMI, FFMI, and BMI [110]. Reproduced under Creative Commons Attribution 4.0 International license (CC–BY). (d) Six hand gestures recorded using EIT for the recognition of human-machine interaction [111]. Reproduced under Creative Commons Attribution 4.0 International license (CC–BY).

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4.2. Cardiovascular and fluid dynamics monitoring

With AI greatly enhancing its diagnostic and prognostic capabilities, transthoracic BIA has emerged as a crucial procedure for monitoring fluid status in cardiovascular and renal disorders. AI-driven models offer accurate evaluations of conditions such as pulmonary edema in heart failure and fluid overload in renal disease by using BIS to measure extracellular and intracellular fluid shifts. Combining transthoracic BIS parameters (specifically $R_0 - R_\infty$) with heart rate variability data in a cubic SVM classifier enabled the detection of acute pulmonary edema with 92% accuracy [103]. In this evaluation, acute decompensated heart failure hospital admission served as the primary clinical diagnostic classification endpoint, while radiographic chest scoring was incorporated as a parallel, qualitative reference modality rather than a definitive analytical standard. While these algorithmic architectures demonstrate promising classification accuracy under internal cross-validation, their clinical utility remains unproven. Retrospective or short-term observational classification does not directly translate into reduced hospitalization rates or improved clinical outcomes. Demonstrating tangible clinical benefit will require prospective, multi-center trials evaluating whether bioimpedance-guided therapeutic adjustments improve morbidity or mortality endpoints compared to standard clinical care.

4.3. Oncology and tissue characterization

By leveraging variations in membrane capacitance and conductivity, electrical impedance spectroscopy discriminates between malignant and benign tissues, with AI significantly enhancing diagnostic precision through advanced classification frameworks [112]. In gynecological applications, a multi-electrode BIS probe demonstrated 94.3% sensitivity and 90% accuracy for cervical intraepithelial neoplasia, which was validated against tissue examination (the clinical reference standard) of excised surgical specimens [113]. In oral oncology, Lin et al. evaluated a CNN classifier for oral tissue staging against surgically punch biopsy histopathology as a diagnostic reference standard [114]. For lung neoplasms, endobronchial electrical impedance spectroscopy coupled with a linear Support Vector Machine differentiated malignant from benign pulmonary lesions, which was validated directly against bronchoscopic biopsy histopathology as the clinical reference standard [115]. In breast oncology, the BiaCanDet space-time attention framework achieved 93.37% classification

accuracy for tumor differentiation, utilizing postoperative histology as the definitive clinical reference standard and clinical ultrasound as an adjunct comparative imaging modality [116–118]. Finally, Carobbio et al. evaluated a needle-based bioimpedance sensing device paired with AI classifiers for detecting head and neck squamous cell carcinoma. Their approach achieved accuracies ranging from 0.67 to 0.93 across tissue types, including mucosa, muscle, and lymph nodes, demonstrating the versatility of AI-BIA in complex anatomical regions [119].

4.4. Wearable and remote monitoring

The advancement of AI has ushered in a new era of seamless, real-time health surveillance for wearable bioimpedance devices, facilitating the non-invasive evaluation of physiological parameters in remote and ambulatory settings [34,120]. With AI algorithms optimizing signal processing and predictive analytics for proactive interventions, these devices are incorporated into form factors such as smartwatches, rings, electronic skins, and patch-based sensors to monitor body composition, hydration status, and hemodynamic indicators such as HRV and blood pressure [35,121,122]. ML-enabled wearable bioimpedance technology enables non-invasive, real-time bladder monitoring, obtaining precise volume and functionality evaluations for improved urological care [123].

In ambulatory settings, wrist-worn bioimpedance prototypes integrated with deep learning architectures, such as convolutional networks and autoencoders, have been explored for tracking autonomic stress responses and estimating body composition trends. When coupled with accelerometry data and adaptive filtering, these multimodal configurations help mitigate dynamic motion artifacts, although translating laboratory-grade classification into robust, population-wide ambulatory monitoring remains an ongoing challenge [35]. Federated learning paradigms offer a promising framework for distributed, privacy-preserving model training across edge devices, demonstrating potential gains in cross-device robustness while preserving localized patient data confidentiality [124]. Using sophisticated integrated circuits and DL, AI-enhanced wearable bioimpedance and biopotential devices enable intuitive human–robot interaction through high-accuracy physiological monitoring and real-time motion intention recognition [125]. These wearables with AI enhancements support longitudinal health profiling in addition to point-of-care diagnostics, transforming passive data acquisition into actionable clinical intelligence for individualized wellness and disease prevention.

4.5. Electrical impedance tomography

With significant implications for lung ventilation monitoring and tumor localization, EIT serves as an advanced modality for visualizing tissue conductivity distributions. AI-driven innovations have further refined the diagnostic fidelity of EIT systems [126]. When integrated with AI and variable ventilation protocols, EIT may support improved respiratory monitoring and potentially contribute to improved clinical management in patients with Acute Respiratory Distress Syndrome by enabling predictive, personalized respiratory strategies [127]. Specifically, U-Net architectures, a class of DL models, have augmented EIT spatial resolution, facilitating real-time visualization of lung fluid dynamics and precise ventilatory monitoring [104]. Furthermore, Deep Reinforcement Learning has been utilized to optimize electrode placement strategies, reducing imaging artifacts and enhancing the robustness of EIT in complex clinical environments [19]. Methodologically, Dimas et al. provided a

comprehensive review of EIT inverse problem solution methods, categorizing the mathematical transition from classical regularized solvers (such as Tikhonov and GREIT) to modern deep learning and sparse Bayesian architectures across static and dynamic imaging scenarios [128].

Unlike zero-dimensional scalar or one-dimensional spectral methods, EIT is a spatial imaging modality that requires solving an ill-posed, non-linear inverse boundary problem to reconstruct 2D or 3D internal conductivity distributions from surface voltage measurements. In this domain, deep learning architectures, specifically CNNs, U-Net variants, and Physics-Informed Neural Networks (PINNs), function as spatial reconstruction engines. These architectures bypass traditional regularized matrix inversions (e.g., Tikhonov or Gauss-Newton routines), suppressing boundary noise artifacts and dramatically enhancing spatial resolution for clinical applications such as dynamic lung ventilation monitoring and tumor localization [86,104,106].

Gomes et al. proposed an EIT image reconstruction method utilizing Extreme Learning Machines to estimate sinograms from electric potential values. When followed by backprojection, this approach achieved results comparable to traditional techniques on synthetic databases, significantly reducing computational load [129]. Advancing the synergy between data and physical laws, Smyl et al. presented a Physics-Informed Neural Network approach for EIT. In non-destructive structural engineering benchmarks on carbon-fiber composite specimens, embedding governing boundary and internal potential PDEs into the loss function yielded lower reconstruction artifact levels than purely data-driven models while achieving an $\approx 80,000 \times$ inference speedup over classical iterative non-linear difference imaging [87,106]. In the domain of wearable diagnostics, Chen et al. and Liu et al. introduced multimodal bioimpedance systems integrated with DL. These frameworks achieve high sensitivity in the real-time monitoring of tissue properties, facilitating the detection of stress and hydration states in ambulatory environments [130,131]. Beyond medical monitoring, Gallardo et al. demonstrated the potential of EIT for HMI applications. By applying PCA and Logistic Regression classification to forearm bioimpedance measurements, they achieved an accuracy of 0.89 for hand gesture recognition while reducing the requisite number of electrodes [111,132]. Collectively, these studies illustrate the potential of AI to support the translation of bioimpedance technologies from experimental research toward clinical and industrial applications, expanding the exploratory scope of EIT-based sensing. However, establishing reliable frameworks for individualized diagnostics and therapeutic monitoring will depend on demonstrating reproducibility across heterogeneous clinical populations. To contextualize reported AI performance metrics and clarify the translational readiness of evaluated frameworks, Table 2 summarizes study-level characteristics across key biomedical applications, delineating sample cohorts, input dimensions, validation pipelines, and multicenter replication status.

Table 2. Study-level methodological and performance context of representative AI-driven bioimpedance applications.

Application & Target	Study Population & Cohort Size (N)	Input Variables / Modality	AI / ML Architecture	Reference / Ground Truth	Validation Scheme	Principal Reported Metric	Validation Level & Translation Status	Reference
Pulmonary Edema Detection	$N = 32$ healthy patients, $N = 23$ heart failure patients during hospital admission, $N = 17$ heart failure patients during hospital discharge	Transthoracic BIS $(R_0 - R_\infty) + \text{HRV}$	Cubic SVM	Clinical diagnosis & radiographic chest scoring	Leave-one-subject-out cross-validation	Accuracy = 92% (vs. 82% for TBI alone, 75% for HRV alone), Sensitivity = 82.6% ($19/23$ fluid-overload baseline cases), Specificity = 95.9% ($47/49$ non-fluid control/discharge cases)	Internal proof-of-concept; single-center cohort	[103]
Cervical Intraepithelial Neoplasia (CIN) Screening	$N = 123$ (69 suspected CIN; 54 benign hysterectomy controls)	Ex vivo multi-electrode bioimpedance spectroscopy probe (17-pin array; 0.625–100 kHz resistivity spectra)	Reconstructed resistivity difference spectra + Logistic Regression / ROC thresholding	Histopathological diagnosis from conization and hysterectomy specimens	Empirical cohort ROC cutoff optimization	Accuracy = 90.0%, Sensitivity = 94.3%, Specificity = 84.0%	Single-center ex vivo validation on surgically excised tissue; requires in vivo clinical verification	[112]

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Application & Target	Study Population & Cohort Size (N)	Input Variables / Modality	AI / ML Architecture	Reference / Ground Truth	Validation Scheme	Principal Reported Metric	Validation Level & Translation Status	Reference
Minimally Invasive Lung Neoplasm Identification	$N = 102$ (116 lung samples: 29 neoplasm, 87 non-neoplasm)	Endobronchial catheter EIS ($ Z $ and phase angle across 15–307 kHz)	Linear Support Vector Machine	Histopathological biopsy examination	5-fold CV with grid-search hyperparameter optimization	Accuracy = 98.1%, Sensitivity (Recall) = 95.4%, Precision = 96.3%, ROC-AUC = 0.979, Specificity = NR	Single-center in vivo bronchoscopic study; restricted to central lung lesions	[114]
Sarcopenia Screening in Older Adults	$N = 727$ with 658 adults (Dataset 1, 21 sarcopenic) / 672 adults (Dataset 2, 24 sarcopenic)	Segmental MF-BIA + anthropometry (age, sex, BMI)	Artificial Neural Network with 5-iteration ensemble averaging	AWGS 2019 clinical criteria (skeletal muscle mass index + grip strength)	70/30 train/validation split with training-set oversampling	Accuracy = 91.0%, Sensitivity = 100%, Specificity = 91.0%	Single-cohort community health checkup sample	[75]
Structural Damage Localization & Conductivity Mapping in Composites	Structural composite phantoms (16-electrode carbon fiber truss & 20-electrode NACA 4424 airfoil)	Direct-current boundary potential differences under adjacent and snake-like patterns	Physics-Informed Neural Network (PINN)	Finite Element Complete Electrode Model simulations and classical Nonlinear Difference Imaging	Experimental hold-out validation across single/multiple notch defects and drop-tower impact damages	Accuracy = NR, Sensitivity = NR, Specificity = NR, Matches classical NLDI fidelity with $\sim 80,000 \times$ faster inference	Nondestructive engineering evaluation; tested on binary damage distributions	[106]

(NR = not reported)

5. Challenges and limitations

5.1. Model interpretability

The clinical adoption of high-capacity DL models within human BIA frameworks remains constrained by their opaque mathematical structures, commonly referred to as “black-box” systems. To maintain medical accountability, legal responsibility, and professional trust, healthcare providers require transparent, verifiable decision-making tracks before integrating algorithmic outputs into high-stakes clinical workflows. Although deep architectures excel at isolating complex, multi-frequency relationships from raw electrical impedance spectra, they inherently lack visible mechanisms to clarify how specific bioelectrical components drive diagnostic conclusions.

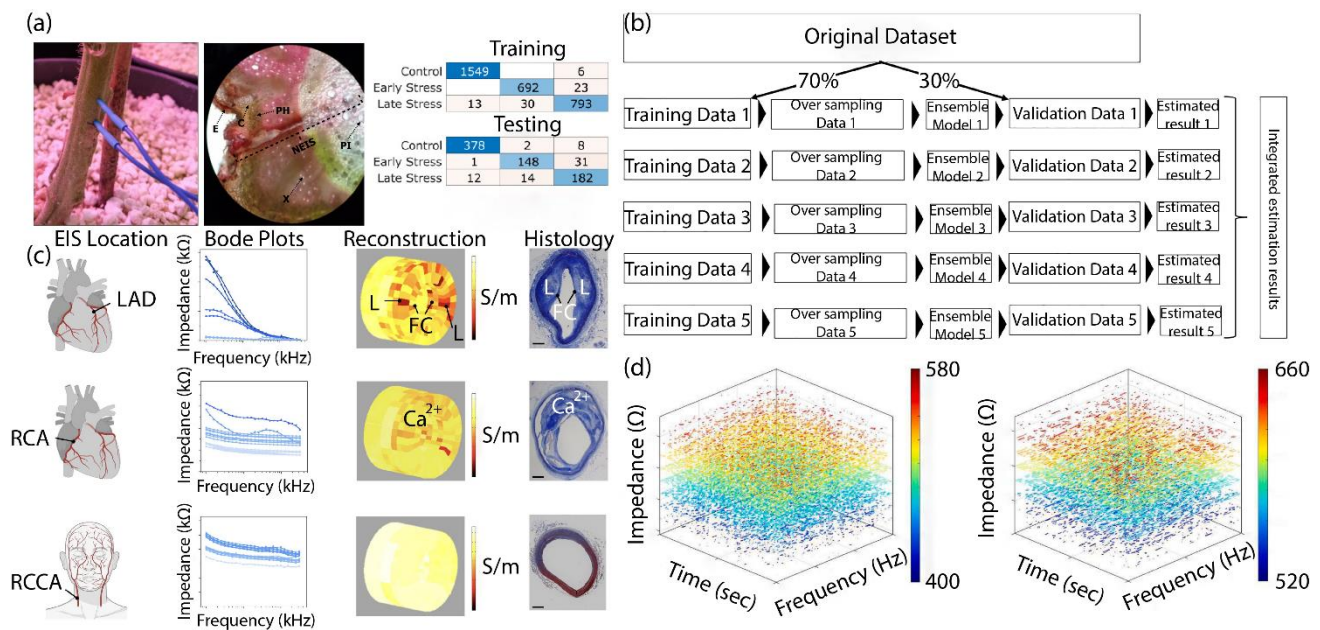


Figure 6. (a) Needle electrode placement in tomato stem with cross-sectional anatomy and confusion matrices showing Cole model classification accuracy for control, early, and late water stress in training and testing datasets [78]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (b) Sarcopenia prediction workflow showing dataset splitting, oversampling for imbalance, ensemble neural network training, and cross-validation [75]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (c) EIT reconstructions from electrical impedance spectroscopy data accurately identify lipid cores, fibrous caps, and calcifications in coronary arteries [133]. Reproduced under Creative Commons Attribution 4.0 International license (CC-BY). (d) 3D bioimpedance spectra of healthy cellular states (left) and stiffened cellular states (right) [134]. Reproduced with permission from Elsevier.

To bridge this interpretability gap, XAI frameworks, most notably SHAP, have been introduced. Grounded in cooperative game theory, SHAP provides model-based feature attributions by calculating the marginal contribution of each input variable to the algorithm’s mathematical prediction relative to a baseline expectation. Critically, SHAP values reflect algorithmic feature importance within a specific

mathematical model and must not be interpreted as causal physiological mechanisms or exact biological weights. For instance, while high SHAP values for a depressed phase angle or low extracellular resistance indicate that the classifier relied heavily on these inputs during pulmonary edema detection, they do not establish direct pathophysiological causality or unconfounded biological weighting. Furthermore, validating these algorithmic attributions across clinical centers remains a major bottleneck: Differences in patient demographics, baseline body geometry, or electrode placement alter model feature-attribution rankings, underscoring that XAI outputs represent conditional statistical explanations rather than invariant biological truths.

An alternative engineering path focuses on deploying inherently interpretable, lower-capacity model architectures, such as shallow convolutional networks or shallow decision tree ensembles. These simplified frameworks provide a controlled balance between predictive accuracy and transparency, leaving their internal branching parameters directly accessible to manual clinical examination. Furthermore, lowering parameter density reduces the mathematical risk of overfitting on highly localized, small clinical data cohorts. To successfully transition AI-driven bioimpedance into standard clinical workflows, developing standardized, domain-specific XAI validation benchmarks remains an essential requirement to ensure algorithmic transparency matches evidence-based medical practice.

5.2. Demographic and environmental variability

The generalizability of contemporary AI models in BIA is severely limited by demographic and environmental confounding factors. Most active algorithmic frameworks are optimized on homogenous datasets derived predominantly from Western cohorts. However, baseline bioelectrical properties exhibit significant variations across global populations due to underlying discrepancies in ethnicity, age, and sex. For example, South Asian populations frequently demonstrate higher absolute resistance values than Caucasian populations due to variations in body geometry and lower average skeletal muscle mass. If training datasets do not explicitly account for these multi-ethnic variations, ML models yield systematic calibration offsets, inflating estimation error (RMSE) and widening limits of agreement in global body composition predictions [135]. Similarly, pediatric and geriatric cohorts demonstrate distinct multi-frequency impedance profiles caused by age-related disparities in tissue density and TBW distribution. These physiological shifts require demographically tailored algorithms to prevent systematic prediction bias and wider limits of agreement [136]. Furthermore, environmental conditions introduce substantial measurement noise. Ambient temperature fluctuations directly alter skin conductivity, while rapid postural adjustments induce gravitational fluid shifts between internal compartments. Collectively, these unconstrained external factors can induce a variance of up to 15% in raw impedance readouts [4].

To mitigate these operational vulnerabilities under dynamic tracking conditions, multi-scale flexible bioimpedance sensing arrays have been integrated with causal hierarchical ML to support continuous, real-time physiological monitoring [134]. However, the compilation of universally applicable, demographically diverse training sets is restricted by high institutional acquisition barriers. To illustrate the integration of diversity protocols into analytical designs, the Kasama Study examined a cohort of 727 community-dwelling older adults aged 65 to 85 years. By incorporating sex, age, height, and BMI alongside segmental MF-BIA configurations, the predictive framework accounted for cross-population lifestyle variability to isolate sarcopenia under real-world conditions [75]. Similarly, Chen

et al. addressed structural variability by evaluating EIT datasets from 20 patients diagnosed with coronary artery disease, demonstrating that standardized boundary voltage measurements maintain model stability across varying baseline metabolic states [133]. Beyond architectural diversity, contextualizing reported performance metrics represents an urgent translational requirement. Across contemporary biomedical AI-BIA literature, high classification accuracies (often exceeding 90–95%) are frequently reported from small, single-center cohorts ($N < 100$) relying on random sample-level data splits. Because multi-frequency impedance profiles obtained repeatedly from the same individual exhibit high intra-subject correlation, sample-level splitting introduces severe data leakage, artificially inflating validation metrics. To transition AI-BIA from proof-of-concept demonstrations to demonstrated clinical translational potential, researchers must mandate patient-level partitioning (e.g., leave-one-subject-out cross-validation), enforce independent multi-center external validation, and benchmark algorithms against clinical reference standard methods under unconstrained ambulatory noise.

In Figure 6, Panel (a) presents the detection of water stress stages in tomato plants using EIS measurements and Cole model classification with histological validation. Panel (b) illustrates ensemble modeling workflow for sarcopenia prediction from bioimpedance data with oversampling techniques. Panel (c) provides impedance spectra and EIT reconstructions for coronary artery plaque characterization (lipid core, fibrous cap, and calcification). Panel (d) shows 3D visualization of impedance dynamics across time and frequency for tissue state differentiation. Resolving these demographic and environmental variances through the deployment of inclusive data libraries and adaptive AI pipelines remains a primary requirement to ensure equitable algorithmic performance and to establish bioimpedance as a trustworthy platform for global precision healthcare [137,138].

Crucially, machine learning frameworks cannot serve as a panacea for poor front-end measurement physics. In ambulatory and wearable environments, motion-induced electrode displacement, variable contact pressure, and sweat-induced impedance collapse generate signal corruptions that fall outside the physiological manifold of standard laboratory training sets. While multimodal sensor fusion such as coupling bioimpedance with accelerometry or contact-pressure sensors provides contextual motion gating, training protocols must explicitly incorporate physically corrupted and motion-degraded spectra. Establishing standardized physical calibration routines and real-time signal quality indices at the hardware level remains essential to prevent algorithmic overfitting to acquisition artifacts.

6. Conclusions

The integration of AI into bioimpedance analysis encompassing classical BIA, spectral BIS, and spatial EIT expands the methodology beyond static empirical regression into dynamic, multi-parametric physiological modeling. By deploying machine learning for numerical Cole parameter fitting, deep neural networks for non-linear boundary reconstruction, and explainable architectures for tabular clinical risk stratification, AI offers potential approaches to mitigate the historical limitations of linear baseline equations under defined experimental conditions. However, transitioning these computational frameworks from exploratory proof-of-concept demonstrations to demonstrated clinical translational potential necessitates a prioritized, translational research agenda: establishing standardized data acquisition protocols (controlling for posture, ambient temperature, and skin-electrode contact mechanics) to minimize front-end physical confounders; enforcing subject-

independent validation schemes (such as patient-wise leave-one-subject-out or nested cross-validation) to eliminate performance inflation caused by autocorrelated bioimpedance measurements; creating open-access, multicenter benchmark datasets across diverse demographic and clinical strata; embedding uncertainty quantification (via Bayesian inference, conformal prediction, and physics-informed neural networks) to output calibrated confidence bounds for high-stakes clinical decision-making; and ensuring algorithmic reproducibility through prospective external validation against definitive reference standards (such as DXA, isotope dilution, or histopathology) to substantiate real-world diagnostic efficacy.

Use of generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The author declares no conflicts of interest in this paper.

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