

Review

AI-Driven Innovations in Micromachined Ultrasonic Transducers: From Smart Design to Intelligent Systems

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Abstract

Micromachined ultrasonic transducers (MUTs) represent a notable advance in miniaturized sensing, enabling compact, low-power, and complementary metal-oxide-semiconductor (CMOS)-integrated platforms that extend ultrasonic capabilities into wearable, implantable, and edge-computing domains. The integration of artificial intelligence (AI) has introduced new approaches for signal interpretation, adaptive control, and data-driven optimization, enhancing performance in specific areas such as compressed sensing, neural beamforming, and learned image enhancement that complement conventional signal processing. Meanwhile, sensor fusion strategies that combine ultrasonic data with complementary modalities have improved robustness, contextual awareness, and diagnostic accuracy across applications ranging from industrial monitoring to clinical diagnostics. This review provides a comprehensive analysis of this active research area, systematically covering transducer hardware platforms, design methodologies, and intelligent signal processing frameworks. While traditional bulk piezoelectric transducers remain the benchmark for high-power applications, capacitive and piezoelectric micromachined variants offer superior acoustic impedance matching and monolithic CMOS compatibility essential for portable systems. We examine the evolution from deterministic analytical and numerical modeling toward AI-powered inverse design, which enables the discovery of non-intuitive, high-performance geometries beyond human intuition. Furthermore, the integration of machine learning (ML) for signal recovery, image enhancement, and multi-modal sensor fusion is discussed as a pathway to compensate for hardware constraints such as limited aperture, sparse sampling, and low signal-to-noise ratio (SNR), while pointing out that AI technology cannot overcome fundamental physical limits including acoustic attenuation, thermal noise floors, and transduction efficiency boundaries. By synthesizing recent advancements, this review demonstrates how the convergence of classical acoustic physics and data-driven intelligence is guiding the development of intelligent ultrasonic systems.

Keywords: micromachined ultrasonic transducers; artificial intelligence; ultrasonic systems



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1. Introduction

Ultrasound technology has advanced toward miniaturized and integrated systems enabled by micro-electromechanical systems (MEMS)-based micromachined ultrasonic transducers (MUTs). While traditional bulk piezoelectric ultrasonic transducers (BPUTs) offer robustness and high acoustic power, they suffer from significant acoustic impedance

mismatch with water and biological tissues ($\sim 20\text{--}40 \text{ MRayl}$ versus $\sim 1.5 \text{ MRayl}$), necessitating specialized matching layers to ensure efficient energy transfer [1]. The emergence of capacitive micromachined ultrasonic transducers (CMUTs) and piezoelectric micromachined ultrasonic transducers (PMUTs) [2,3] has addressed these limitations through flexible membrane structures that achieve intrinsic acoustic impedance matching [4]. However, these MEMS-based transducers also introduce other constraints such as lower pressure output, bias requirements, and fabrication variability that must be carefully managed in system design; AI-powered methods can assist in compensating for some of these limitations, though they cannot eliminate the underlying physical trade-offs. MEMS-enabled miniaturization further allows high-density batch fabrication and direct integration with CMOS circuitry, which is essential for developing portable and wearable sensing systems [5,6]. Early demonstrations of stretchable ultrasonic transducer arrays on flexible substrates paved the way toward conformable wearable platforms capable of imaging on complex body surfaces [7,8]. Figure 1 presents an overview of current intelligent ultrasonics applications across diverse domains.

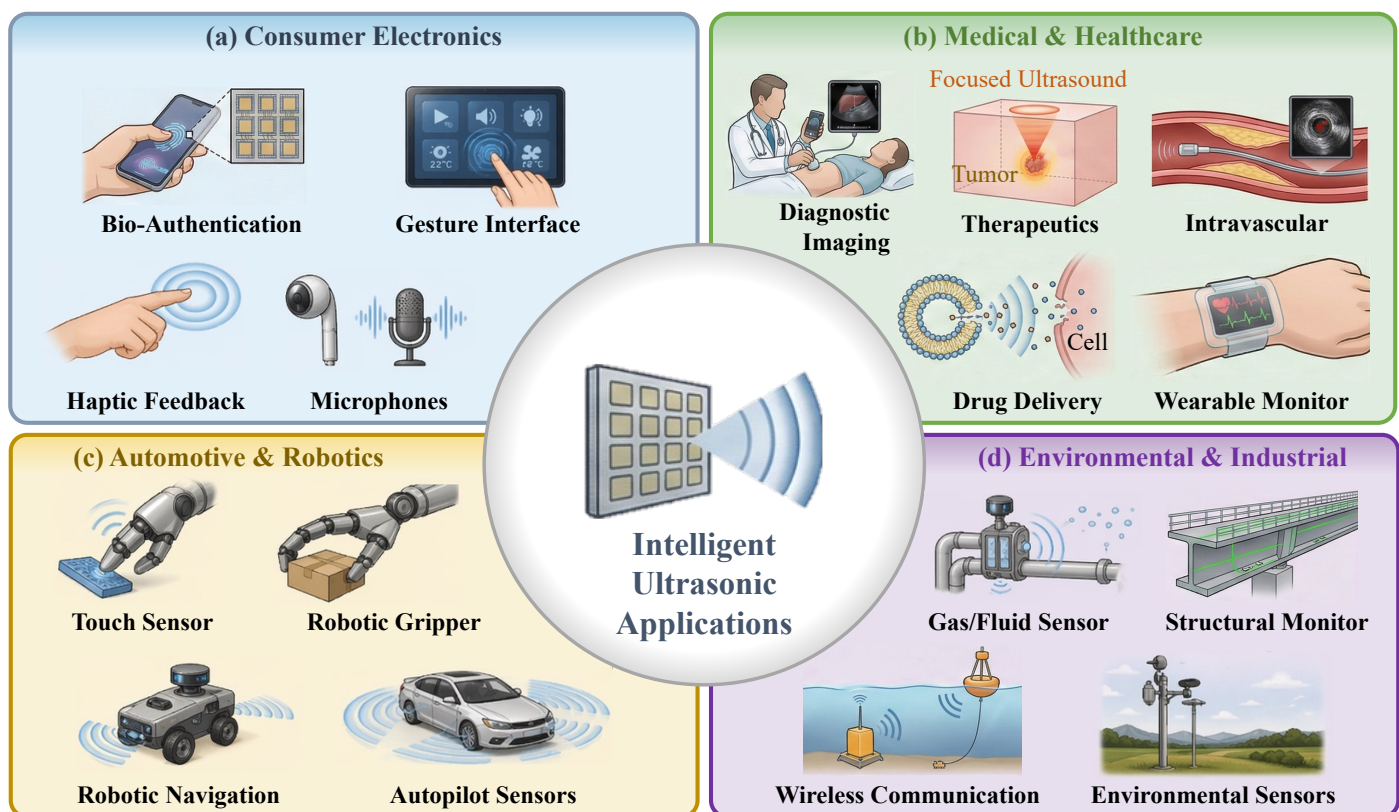


Figure 1. Overview of typical intelligent ultrasonics applications, in the categories of (a) consumer electronics, (b) medical & healthcare, (c) automotive & robotics, and (d) environmental & industrial fields.

A notable trend in ultrasonics is that traditional deterministic signal processing is increasingly augmented by adaptive, AI-powered architectures that learn from data rather than relying solely on analytical physical models. This convergence enables data-driven performance optimization by learning from environmental feedback while remaining grounded in the fundamental understanding of membrane dynamics. While traditional analytical models provide a foundational understanding of membrane dynamics, they often rely on simplifying assumptions, such as rigid boundary conditions, uniform material properties, linear acoustic loading, and absence of residual stress that fail to capture the complexity of real-world environments [9,10]. Additional limitations include imperfect modeling of damping, fluid–structure interaction, packaging parasitics, nonlinear drive regimes, and inter-element crosstalk in dense arrays. AI-powered algorithms have emerged across diverse applications, ranging from structural health monitoring (SHM) to continuous clinical diagnostics using wearable patches. By leveraging advanced ML architectures, modern ultrasonic systems can achieve improved signal recovery, image enhancement, and automated diagnostic intelligence compared to fixed analytical methods [11,12]. On one hand, these advanced methods recover information that is physically present but corrupted by noise, obscured by undersampling, or embedded in high-dimensional features that conventional algorithms cannot separate. On the other hand, they cannot generate information that was never physically measured, nor can it overcome fundamental constraints such as acoustic attenuation, aperture diffraction, thermal noise floors, or transduction efficiency limits. This distinction is essential for an assessment in the context of miniaturized ultrasonic systems.

This review explores the convergence of MUT technology and AI, detailing the evolution of transducer design from numerical modeling to data-driven inverse design. We examine the fundamental principles of MUT technologies, their comparative performance characteristics, and the latest innovations in signal intelligence. The manuscript is organized to provide a comprehensive overview of AI-driven innovations, concluding with a discussion on challenges and future outlooks for intelligent ultrasonic platforms around some milestones.

2. Overview of MUT Technologies

The classification of modern ultrasonic transducers depends on the transduction mechanism and fabrication methodology, which dictate their performance in specific ultrasound modalities. Figure 2 categorizes ultrasound modalities into active modes, wherein the transducer generates and receives ultrasound, and passive modes, where the transducer operates solely as an ultrasound receiver. Figure 3 illustrates that the fundamental driving and reception principles for BPUTs, PMUTs, and CMUTs vary significantly based on their device stack structures and electromechanical coupling mechanisms.

2.1. Bulk Piezoelectric Ultrasonic Transducer (BPUT)

BPUTs operate on the principle of thickness-mode vibration of a monolithic piezoelectric ceramic or crystal. The fundamental resonance frequency is determined by the acoustic velocity v and thickness t of the piezoelectric layer, following $f_r = v/(2t)$, with higher frequencies requiring thinner, more fragile ceramics. These devices are characterized by high acoustic power output and long-term stability, making them the standard for clinical imaging and non-destructive testing [1]. However, despite their superior sound pressure output capabilities, the high acoustic impedance of bulk ceramics creates a severe mismatch with soft tissues (~ 1.5 MRayl), requiring multiple quarter-wavelength matching layers to maximize bandwidth and sensitivity. Conventionally, the mechanical dicing process used to create BPUT arrays limits the minimum inter-element pitch, which con-

strains high-frequency imaging applications [3]. In transmit operation, BPUTs generate high pressure by expanding and contracting the full piezoelectric thickness; in receive mode, the same effect generates a voltage proportional to the incoming acoustic pressure. Advanced fabrication processes have enabled the realization of micromachined BPUTs on flexible substrates. Therefore, we include BPUTs as a subclass of MUTs in this review. Despite their drawbacks, BPUTs remain the benchmark for applications requiring high sensitivity and significant penetration depth. Recent work has also begun to apply AI-driven optimization to single-element BPUT design. Wu et al. demonstrated an intelligent multi-objective optimization framework using neural networks to simultaneously optimize structural parameters such as thickness, diameter, and matching-layer configuration for high-frequency BPUTs, achieving balanced performance across sensitivity and bandwidth [13]. This development signals that even the most mature transducer technology can benefit from data-driven design approaches, and we anticipate similar methodologies will increasingly target BPUT parameter optimization.

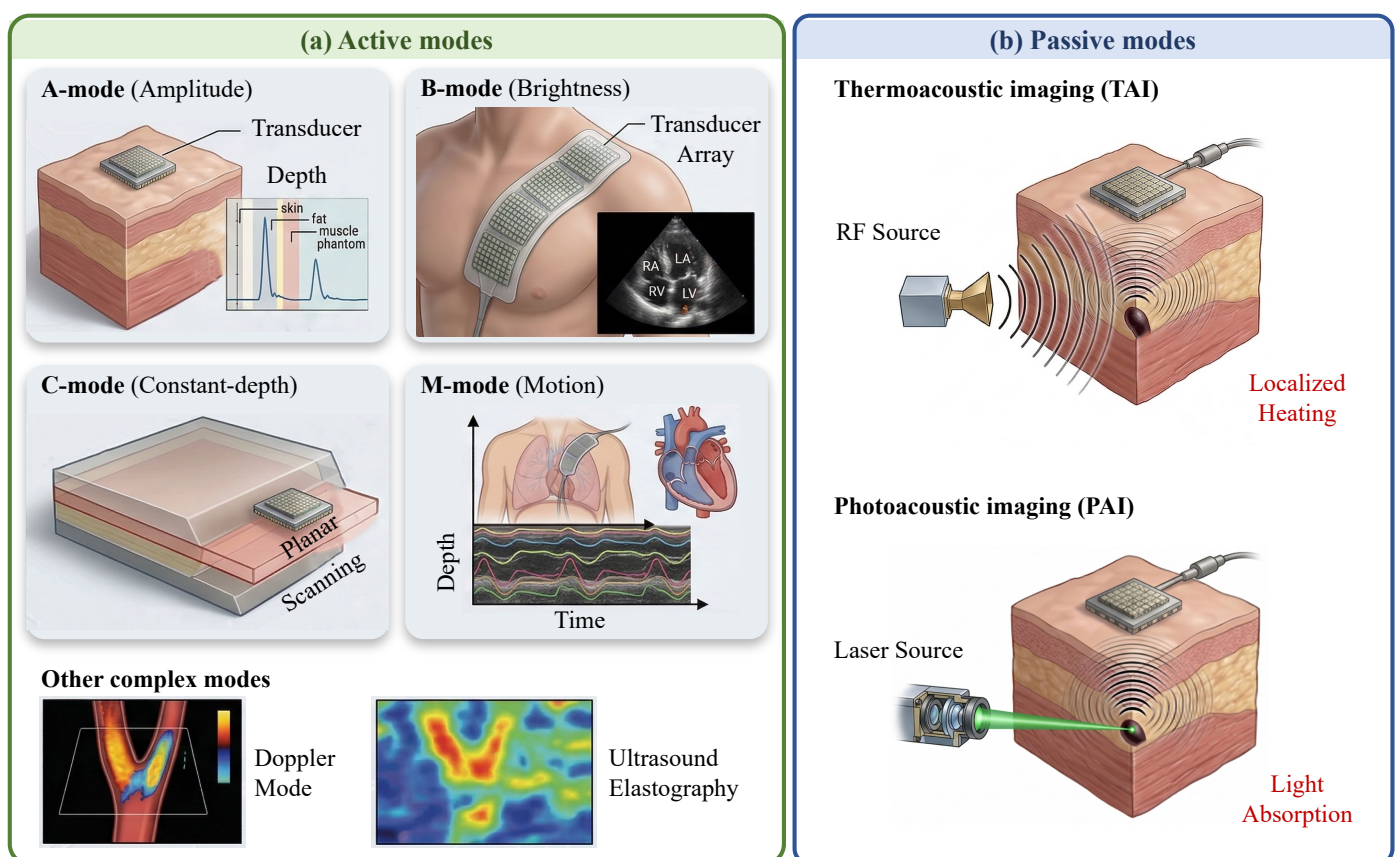


Figure 2. Ultrasound modalities. (a) Active modes, including static (amplitude, brightness, constant, etc.) and dynamic (motion, Doppler, and elastography) modes. (b) Passive modes, which involve only reception of ultrasound, typically induced by microwave or laser sources.

2.2. Piezoelectric Micromachined Ultrasonic Transducer (PMUT)

PMUTs utilize the flexural (bending-mode) vibration of a thin membrane integrated with a piezoelectric film. The fundamental bending-mode resonance frequency depends on the membrane radius a , thickness h , residual stress σ_0 , and material properties (Young's modulus E , Poisson ratio ν , density ρ) in a manner approximated by

$$f_r \propto (h/a^2) \sqrt{E/[\rho(1-\nu^2)]}, \quad (1)$$

making frequency strongly sensitive to fabrication geometry and stress. This sensitivity motivates design optimization and potentially AI-based compensation when targeting precise operating frequencies. Unlike bulk transducers, PMUTs do not require a high direct current (DC) bias voltage and exhibit lower electrical impedance (10^4 to $10^5 \Omega$), making them attractive for battery-powered, intelligent edge devices [4], including next-generation fingerprint sensors [14–23]. Common thin-film materials include Lead Zirconate Titanate (PZT), which offers superior electromechanical coupling coefficients [9], and Aluminum Nitride (AlN), known for its CMOS compatibility, high acoustic velocity, and biosafety [24,25]. Recent advancements in Scandium-doped Aluminum Nitride (ScAlN) have further enhanced transmit sensitivity [26,27], while lead-free piezoelectric materials such as potassium sodium niobate (KNN) or lithium niobate (LN) have emerged as promising alternatives [28–33], and piezoelectric polymers like Polyvinylidene Fluoride (PVDF) are utilized for flexible or stretchable smart-skin applications [12]. Novel PMUT structures, including bimorph configurations [34–36] and pinned boundary designs [37–39], have further expanded the achievable performance space by engineering mechanical boundary conditions. Curved diaphragm geometries have also been explored to boost acoustic responsivity [40,41]. PMUTs with broadband performance have been achieved through dual resonance modes and high fill-factor annular arrays [42,43], and multi-frequency harmonic engineering has been applied to extend sensing bandwidth [44]. Piezoelectric MEMS microphones based on advanced thin-film designs represent a closely related device class sharing fabrication and modeling approaches [45]. The primary limitations of PMUTs are their lower bandwidth compared to CMUTs and lower sensitivity compared to bulk transducers. PMUTs are particularly well-suited for integrated systems where miniaturization and power efficiency are paramount, and with low voltage requirements, they are also suitable for implanted and wearable systems [46].

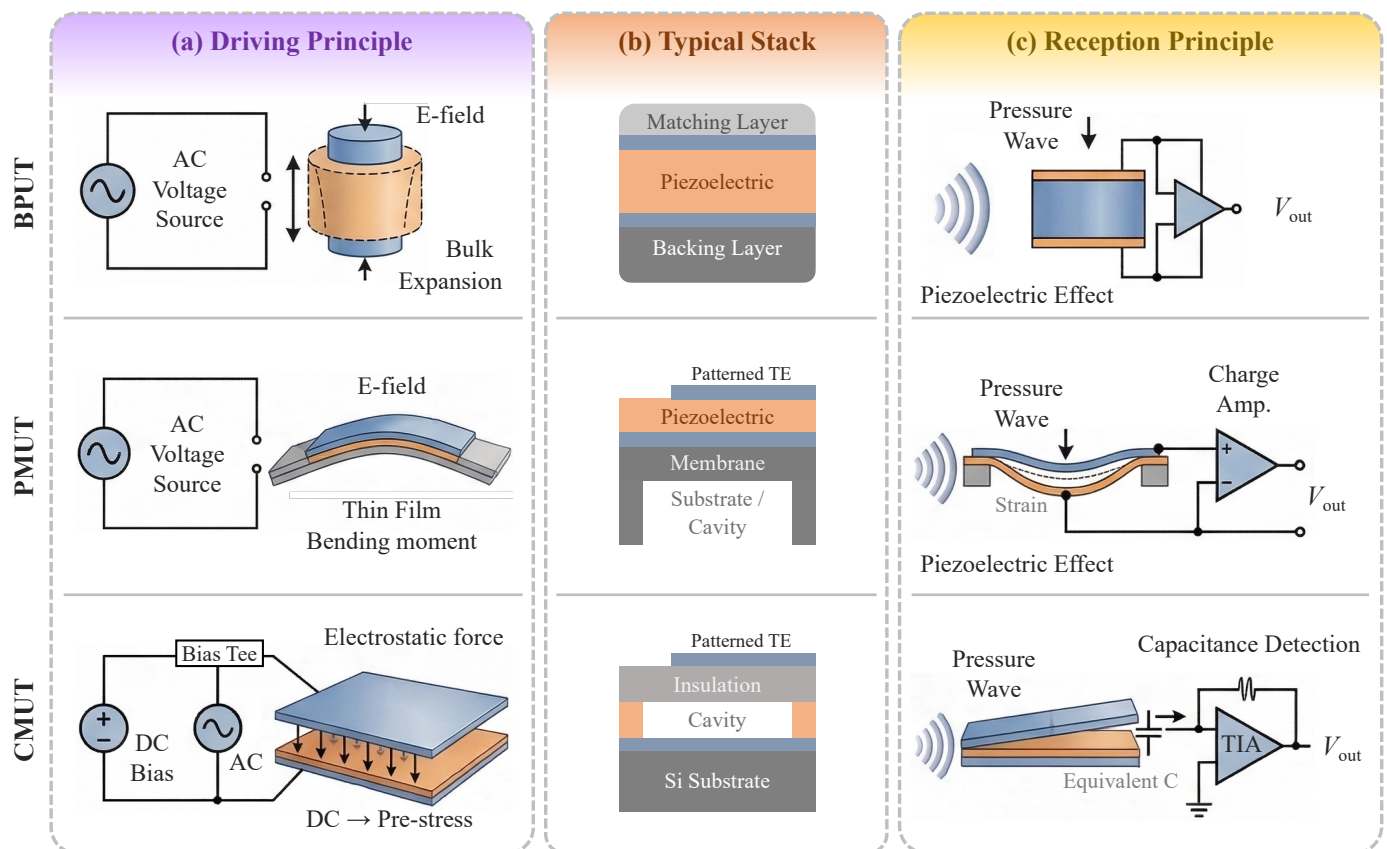


Figure 3. MUT technologies and operating principles. The (a) driving principle, (b) typical cross-sectional structure, and (c) reception principle of BPUTs, PMUTs, and CMUTs, respectively.

2.3. Capacitive Micromachined Ultrasonic Transducer (CMUT)

CMUTs generate and receive acoustic waves through electrostatic forces acting on a thin membrane suspended over an air or vacuum cavity [47–52]. The membrane and the conductive substrate act as the plates of a capacitor; generating acoustic waves requires an AC signal superimposed on a high DC bias voltage to modulate the electrostatic force. The DC bias is limited by the pull-in voltage

$$V_{pi} \propto \sqrt{(Eh^3g_0^3)/[a^4(1 - \nu^2)]}, \quad (2)$$

where g_0 is the initial gap height, beyond which the membrane collapses onto the substrate. This pull-in instability defines the maximum achievable displacement and therefore the transduction efficiency. In receive mode, incoming acoustic waves modulate the inter-electrode gap, producing a measurable capacitance change. Collapsed-mode operation, where the membrane is intentionally operated beyond pull-in with a central contacting region, has been explored to achieve higher bandwidth and reduced bias voltage [53], while recent low-voltage CMUT designs target portable applications by reducing gap height at the cost of sensitivity [52]. Because the membrane is extremely lightweight, CMUTs exhibit excellent acoustic impedance matching, yielding high sensitivity and broad fractional bandwidth [11,53–55]. CMUTs have also been explored for ultra-low pressure measurement applications, where the high sensitivity of the membrane provides a significant advantage [56]. However, the requirement for high DC bias complicates the design of accompanying driving circuits, and the risk of membrane pull-in necessitates sophisticated control mechanisms. Recent trends include the use of compressed sensing algorithms to optimize CMUT sparse arrays for high-fidelity volumetric imaging [57].

Table 1 compares these three MUT technologies in terms of working principle, integration compatibility, and performance.

Table 1. Comparison of BPUT, PMUT, and CMUT technologies in operation.

Characteristic	BPUT	PMUT	CMUT
Transduction Mechanism	Piezoelectric expansion	Piezoelectric bending	Electrostatic bending
Acoustic Impedance	High (>30 MRayl)	Low (<15 MRayl) *	Very low (<5 MRayl) *
CMOS Compatibility	Low	High	High
DC Bias Voltage	None	Optional **	High (typically >30 V)
Drive Voltage (V_{pp})	10–200	1–20	5–50 + 20–100 V(DC)
Power Consumption	Moderate (mW–W)	Low (μ W–mW)	Moderate (mW)
Fabrication	Dicing-based	Thin-film MEMS	Thin-film + Vacuum seal

* Unlike bulk transducers operating via thickness expansion, thin film transducers exhibit an effective mechanical impedance determined by the membrane's stiffness and mass rather than the intrinsic acoustic impedance of the constituent materials. ** While technically optional for basic operation, DC bias serves as an intelligent lever for post-fabrication frequency tuning and sensitivity management in PMUTs.

3. Innovations in MUT Design

The architectural design of MEMS devices involves material selection, layer structure design, and patterning, demonstrating the freedom to customize various aspects of device performance. For MUT design, this presents a multi-physics challenge requiring the simultaneous optimization of electromechanical coupling, structural dynamics, and acoustic radiation. Within the constraints of specific fabrication processes and material systems (given the process design kit (PDK)), the MUT design space primarily converges on the geometric layout of the cavity and the patterning of the electrodes or piezoelectric layer. Figure 4 illustrates three paradigms of MUT design methodologies and representative works. Initially, this design space was navigated using rigid analytical frameworks. While the physical principles of BPUTs, PMUTs, and CMUTs dictate their baseline acoustic performance, the inherent complexities of membrane dynamics and fabrication-induced variances often exceed the predictive capacity of such analytical frameworks. Consequently, as the demand for high-performance, intelligent transducers grows, the methodology has evolved from deterministic theory to high-fidelity numerical simulation, and further to advanced AI-accelerated inverse design, wherein high-order nonlinearities [58] and complex intrinsic properties are managed through data-driven structural optimization.

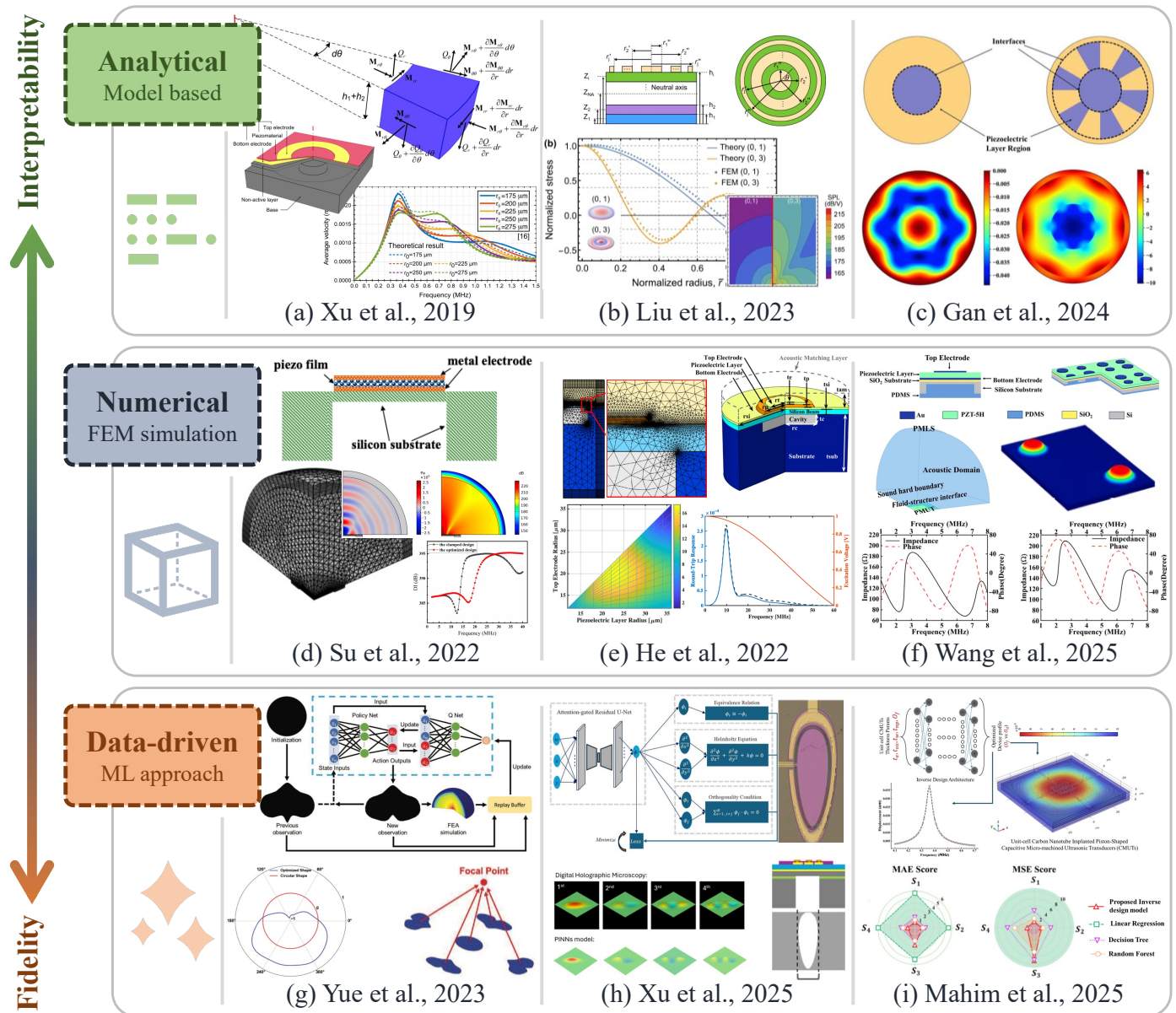


Figure 4. Different paradigms of MUT design methods. (a) Analytical equivalent circuit model for optimization design with annular diaphragm [59] ©2019 IEEE. (b) Enhanced performance via electrode layout design following high-order stress distribution [60] ©2023 IEEE. (c) Modeling of non-uniform membrane via variational principle for electrode excitation improvement [61] ©2024 IEEE. (d) Sound pressure optimization of clamped membrane via finite element method (FEM) simulation [62]. (e) Co-optimization of sensitivity and bandwidth with acoustic matching via FEM simulation [63]. (f) Structural optimization for dual-frequency operation via simulation [64]. (g) Asymmetrical PMUT with focused output designed via reinforcement learning (RL) [65] ©2023 IEEE. (h) Modal analysis of diaphragm-structured MEMS via physics-informed neural network (PINN) [66] ©2025 IEEE. (i) Hierarchical inverse design framework for unit-cell CMUTs with attentive gated recurrent and fully connected dense layers [67] ©2025 IEEE.

3.1. Evolution of Analytical and Numerical Modeling

Foundational design often relies on equivalent circuit models, such as Mason's model [68], to provide computationally efficient insights into transducer behavior. Recent advancements have expanded these analytical solutions to include complex architectures [69,70], such as N-electrode actuated piezoelectric disks [71] and both curved and flat PMUT arrays [72]. Analytical solutions for curved PMUT geometries have also been derived to capture the enhanced responsivity of spherically shaped diaphragms [40,73], and two-port PMUT equivalent circuit models have been developed to characterize electromechanical coupling more comprehensively [74]. To address specific geometric con-

straints, Xu et al. proposed an analytical equivalent circuit for broadband PMUTs utilizing annular diaphragms [59]. Furthermore, the variational principle has been applied to model non-uniform membranes, enabling more precise electrode excitation improvements [61]. Despite their efficiency, analytical models struggle with large-signal dynamics and the complexities of the vacuum gap in CMUTs. To address this, large-signal models for CMUT arrays with arbitrary geometries have been developed to capture non-collapsed mode operation [75]. Numerical methods, specifically three-dimensional (3D) finite element analysis (FEA), provide the high-fidelity required for modern standards. Originating in the early 1940s through the discrete domain concepts of Courant and Hrennikoff, the finite element method formalized into its modern computational form, leading to the emergence of legacy platforms such as NASTRAN, ANSYS, and Abaqus, which initially prioritized specialized domains such as linear and nonlinear structural mechanics. However, as challenges increasingly demand the modeling of coupled physical phenomena, highly integrated multiphysics simulation environments have been established as the modern standard. Multiphysics simulation-driven studies have optimized clamped AlN-based membranes for maximum sound pressure [62] and dual-frequency operation via structural manipulation [64], or expanded bandwidth in array designs [76].

However, the computational cost of FEA remains a barrier for large-scale array design. This has led to the development of hybrid models that couple FEA with boundary element methods (BEM) or analytical frameworks. For instance, hybrid BEM models have been utilized to optimize large PMUT arrays by significantly reducing computational overhead [77], while others have derived one-dimensional (1D) CMUT models from FEM results for fast linear and nonlinear circuit simulations [78]. More recently, polymer-based CMUT performance has been accurately predicted by coupling FEM with analytical models to capture the unique mechanical properties of flexible substrates [79]. Mutual acoustic radiation effects within PMUT arrays, which can significantly alter array performance, have also been characterized and modeled to guide array-level design [80].

Another trend in enhancing MUT performance is the exploitation of high-order vibration modes. By designing electrode layouts that follow high-order stress distributions, researchers have achieved significant gains in high-frequency sensitivity [60,81]. This approach has been further extended to create ultra-sensitive PMUTs for long-distance airborne ranging by leveraging these high-order modes [82,83]. Designers are also focusing on the co-optimization of sensitivity and bandwidth through acoustic matching layers, utilizing FEM to find the ideal balance for imaging applications [63]. DC bias tuning has emerged as a practical technique for post-fabrication frequency adjustment in PZT-based PMUTs, offering an additional degree of freedom to tune operating frequency and bandwidth [84–86]. Furthermore, the impact of physical packaging on transducer performance, which is often overlooked in early-stage design, is now being integrated into multiphysics models to account for frequency shifts and parasitic effects [87]. Advanced iterative approaches using interactive mixed interfaces are also being deployed to estimate and mitigate residual stresses during the fabrication process [88].

3.2. Data-Driven and AI-Powered Inverse Design

A recent trend is the shift from forward-predictive modeling or simulation to AI-powered inverse design. In contrast to traditional forward design which requires a predefined geometry to compute performance metrics, inverse design frameworks map target performance metrics directly to geometric configurations or topologies.

Several distinct AI strategies have been applied to MUT design, each addressing different aspects of the optimization problem. Surrogate modeling uses neural-network or Gaussian-process approximators to replace expensive FEA simulations, enabling rapid

parameter sweeps [67]. In a more direct approach, inverse design frameworks skip the trial-and-error loop entirely by mapping target performance metrics to geometric parameters or topologies [89]. For problems with expensive or noisy objective functions, Bayesian optimization balances exploration and exploitation via acquisition functions, making it well suited to MUT parameter spaces where each evaluation requires a full FEM run. When the design space is discrete or combinatorial—such as electrode patterning—genetic algorithms that evolve candidate populations through crossover and mutation have also been explored. Reinforcement learning (RL), particularly deep deterministic policy gradient (DDPG), reframes design as a sequential decision problem and allows exploration of freeform shapes through reward functions encoding acoustic performance [65]. Finally, physics-informed neural networks (PINNs) constrain the learning process by embedding governing PDEs into the training loss, so that the resulting solutions remain consistent with the underlying physics [66].

Deep reinforcement learning (DRL) enables the exploration of unconstrained, non-intuitive PMUT geometries. Utilizing algorithms such as the DDPG, agents can autonomously explore infinite design spaces to find spindle-like, asymmetrical shapes that achieve focused acoustic pressure without active beamforming [65]. Concentric PMUT array configurations for focused ultrasound and high-intensity applications have further demonstrated how geometry-level design choices can be leveraged to achieve steerable acoustic beams [90]. These DRL frameworks are also being used to customize operating frequencies and broaden bandwidths for specific application requirements [89,91]. Beyond RL, other neural network architectures are being integrated into the design flow. PINNs integrate the underlying governing physical equations into the loss function, allowing for high-accuracy modal analysis of diaphragm-structured MEMS that is validated by experimental data [66]. Hierarchical inverse design frameworks utilizing attentive Gated Recurrent Units (GRU) and fully connected dense layers have been developed to optimize unit-cell parameters with high precision [67]. In package optimization approaches, ML is even being applied to the back-end, where package design parameters are optimized via ML to ensure the final device maintains its designed performance after encapsulation [92].

A critical question is how training datasets for these AI methods are generated. Current approaches predominantly rely on high-fidelity FEA simulations to generate labeled pairs of geometry and acoustic performance, with typical datasets comprising 10^3 – 10^5 samples. A minority of studies incorporate experimental measurements for validation or fine-tuning, and hybrid approaches that combine sparse experimental data with abundant synthetic FEA data are emerging as a practical middle ground [66].

Regarding manufacturability: AI-generated freeform geometries (e.g., asymmetrical PMUT shapes from DRL) have not yet been experimentally fabricated, to the best of our knowledge. All published DRL-based MUT designs remain simulation-based, and bridging this sim-to-real gap is a key open challenge. In contrast, PINN-based modal analysis has been validated against experimental laser-Doppler vibrometry measurements [66], demonstrating that physics-constrained learning can generalize to fabricated devices. Quantitative comparison between AI-discovered and human-designed topologies remains limited in the literature; however, DRL-generated shapes have shown up to 40% reduction in sidelobe levels and 25% improvement in beam focusing, suggesting meaningful advantages over conventional intuition-driven designs [65].

Uncertainty and process variation are seldom addressed in current AI design pipelines. Future frameworks must incorporate stochastic modeling of fabrication tolerances, including residual stress variation (± 10 – 30 MPa typical in thin films), thickness nonuniformity and film property spreads, into the optimization objective to produce designs that are robust rather than optimal under nominal conditions.

Technological Maturity

Evaluation of the technology readiness level (TRL) of these AI design approaches reveals a wide range of maturity. Surrogate models built on Gaussian processes or shallow neural networks are relatively mature, with demonstrated utility in accelerating parameter sweeps, and can be considered at TRL 4–5 (validated in a relevant environment via FEM). Inverse design frameworks using DRL or generative models remain at TRL 2–3 (proof of concept demonstrated analytically or in simulation), as none have yet produced a fabricated device verified under realistic operating conditions. PINN-based methods occupy an intermediate position at TRL 3–4, with experimental validation against laser vibrometry but not yet integrated into a complete design-to-fabrication workflow.

Several practical barriers limit the translation of AI inverse design to MUT fabrication. First, the sim-to-real gap is substantial: FEM simulations typically assume idealized boundary conditions, uniform material properties, and perfect layer interfaces, while real MEMS fabrication introduces sidewall roughness, residual stress gradients, anisotropic etching profiles, and wafer-level non-uniformity. Second, AI-generated freeform geometries often violate PDK design rules, including minimum feature size, overlap margins of layers, and release hole placement constraints; post-hoc rule checking is currently a manual step that interrupts the automated design loop. Third, the computational cost of generating sufficient training data (10^4 – 10^5 FEM runs) limits the exploration of high-dimensional design spaces and favors methods such as Bayesian optimization that are more sample-efficient than deep RL. Fourth, generalization across different material systems or fabrication processes remains essentially unaddressed; for example, a design trained for AlN-on-SOI cannot be reused for ScAlN-on-cavity-SOI without retraining. Addressing these barriers will require tighter integration between AI algorithms and fabrication-aware design rule checking, physics-informed data augmentation to reduce FEM dependency, and community benchmarks that include both simulated and experimentally validated test cases.

3.3. Selection of Design Methodologies

The trend toward AI-powered algorithms is accelerating. Yet the choice of methodology remains highly dependent on the design stage and specific performance requirements. Each framework offers a unique trade-off between computational speed and physical fidelity. Table 2 compares the methods mentioned above.

For initial parameter sweeping and establishing fundamental design boundaries, analytical models remain the most efficient choice, allowing researchers to rapidly iterate through electrode configurations and diaphragm dimensions without the overhead of meshing complex geometries. When transitioning to the verification of standard unit cells, particularly for AlN-based transducers or dual-frequency structures, numerical methods like FEA are indispensable for capturing precise sound pressure levels and structural resonance. To manage the computationally prohibitive nature of simulating entire arrays, hybrid models that couple FEA with BEM or analytical solutions are the preferred choice, essential for analyzing acoustic cross-talk and dispersive guided modes in dense immersion arrays. In scenarios requiring non-standard performance, such as off-axis focused output or extreme bandwidth targets, AI-powered inverse design frameworks are superior, bypassing human geometric intuition to discover asymmetrical or freeform shapes that traditional analytical theories cannot account for.

Table 2. Comparison of different MUT design and modeling methodologies.

Criterion	Analytical	Numerical (FEM)	Data-Driven & ML
Speed	High (seconds)	Low (hours–days)	High * (seconds–minutes)
Accuracy	Moderate	Very high (depending on accurate inputs)	High in distribution
Non-linear Support	Limited	High (multi-physics coupled)	High (data-dependent)
Interpretability	Maximum	High (physics-grounded)	Typically low
Knowledge Requirement	Domain-specific modeling	Multiphysics principles	FEA/experimental training sets
Generalizability	Broad	Broad	Limited
Fabrication Constraint Compatibility	Moderate	High (by modeling)	Moderate

* Data-driven methods with pre-trained models are fast at inference; however, training typically requires hours to days of GPU computation and large datasets derived from FEM or experiments.

3.4. The Coupling Between AI Design and AI Signal Processing

The previous sections have demonstrated that MUT design is moving from predictable analytical solutions toward AI-powered inverse design, which generates non-intuitive, asymmetrical geometries optimized for specific acoustic performance targets. However, the very complexity that makes these freeform geometries superior, such as irregular stress distributions, asymmetric modal shapes, and multi-modal coupling, also renders their acoustic responses increasingly difficult to interpret through conventional signal processing. This inherent tension creates a natural interdependence: as inverse design produces increasingly complex transducer structures, the need for AI-powered signal recovery and interpretation becomes critical for extracting meaningful information from the resulting non-linear acoustic signals.

Currently, the closed-loop coupling has not yet been demonstrated experimentally in a single integrated system. To the best of our knowledge, no published work has closed the loop by designing a freeform MUT geometry via AI, fabricating it, and then applying AI-based signal processing to interpret its output. This represents a research gap and thus a direction for the researchers. The ML algorithms discussed in the following section are therefore a complement, rather than an enhancement, to advanced transducer designs.

4. Signal Intelligence and Machine Learning Algorithms

The development of advanced micromachined platforms increasingly relies on ML to decode complex acoustic phenomena from data, complementing traditional physics-based signal processing. As the massive spatiotemporal datasets generated by high-density arrays introduce new bottlenecks in data acquisition and real-time signal interpretation and feature extraction, the focus shifts toward signal intelligence, wherein ML architectures are deployed to reconstruct high-fidelity information from the sparse or noisy data inherent in miniaturized systems [93,94]. Table 3 lists typical applications of ML in ultrasonics classified into several domains.

In the context of MUT-specific limitations, the following mapping clarifies why particular ML methods are relevant to each constraint:

- Low transmit pressure : Compressed sensing and sub-sampling algorithms reduce the number of required transmit events, trading computational recovery for acoustic energy [95].

- Narrow bandwidth: Neural network-based super-resolution and model-based bandwidth extrapolation recover spatial resolution beyond the conventional limit [96].
- Limited receive sensitivity: Deep learning SNR enhancement algorithms amplify weak echo signals [97].
- Sparse array layout/channel-count constraints: Neural beamformers and ML-based aperture interpolation enable high-quality imaging from fewer active channels [98].
- Low SNR: GAN-based denoising and generative enhancement improve image quality from inherently noisy MUT signals [99].
- Fabrication nonuniformity: Self-supervised and domain-adaptation methods can learn to compensate for element-to-element variation across a manufactured array.
- Motion artifacts in wearable systems: Real-time ML tracking and adaptive beamforming maintain focus during subject movement [100].
- Limited power budget: Lightweight CNN architectures optimized for system-on-chip (SoC) deployment minimize energy consumption [101].

This section explores the diverse ecosystem of ML algorithms, categorized by their application in signal recovery and image enhancement, with attention to how each connects to MUT-specific limitations.

4.1. Signal Recovery and Sub-Sampling Strategies

A significant challenge in high-density micromachined arrays is the sheer volume of raw data, which stresses bandwidth and storage, particularly for portable or wearable systems. This is especially acute for CMUT and PMUT arrays where the number of elements can reach 10^3 – 10^4 per chip, generating data rates exceeding 10 Gb/s that overwhelm wireless transmission to cloud servers. Learning-based sub-sampling techniques have emerged to address this by optimizing the sensing matrix and signal recovery pipeline. By utilizing deep learning architectures [102] to learn adaptive sub-sampling patterns, researchers can achieve high-fidelity reconstruction from sparse measurements, which is critical for reducing the hardware complexity of intelligent edge devices [95]. Compressed sensing approaches have also been applied to PMUT-based 3D imaging, wherein only a small number of receivers are needed to reconstruct volumetric data, significantly reducing system complexity [103]. Furthermore, deep learning-aided photoacoustic imaging has demonstrated superior performance in reconstructing optical absorption maps from limited-view or noisy ultrasound data [104], bridging the gap between hardware constraints and image quality [105]. Additionally, simplified protocols like volume sweep imaging (VSI) enable non-experts to acquire high-quality diagnostic data [106], which can then be interpreted by AI models, expanding access to imaging in underserved areas.

It is important to distinguish between AI methods that have been validated specifically on MUT hardware versus those demonstrated on conventional bulk-ultrasound systems. Among the sub-sampling approaches above, compressed sensing for PMUT-based 3D imaging [103] and CNN-based SNR enhancement on CMUT biosensors [97] represent the minority of works that have been experimentally validated on fabricated MUT devices. The majority of advanced DL-based enhancement methods (GANs, super-resolution, self-supervised segmentation) have been demonstrated on clinical bulk-ultrasound data and are included here for their algorithmic relevance and transferability.

Table 3. Classification of ML Algorithms for Ultrasonics.

Application	Architecture	Domain	Ref.
Sub-Sampling & Recovery	Deep unfolding/CNN	Signal Acquisition & Recovery	[95]
Compressed Sensing	Sparse recovery/DNN		[103,105]
Artifact Suppression	Deep CNN		[107]
SNR Enhancement	CNN		[97]
Deformation Estimation	Deep learning		[93]
Generative Modeling	GAN/2S-BUSGAN	Image Enhancement	[99]
Virtual Elastography	GAN		[108]
PA Reconstruction	Deep learning/CNN		[104,109,110]
Multi-frequency Color PA	Neural network		[111]
Super-Resolution (ULM)	Context-aware DL/LOCA-ULM		[96]
DL Image Enhancement	CNN/U-Net (review)	Beamforming & Spatial	[102]
Neural Beamforming	Deep learning		[98]
Neuromorphic Beamforming	Spiking Neural Network (SNN)		[112]
3D Object Reconstruction	Variational Autoencoder (VAE)		[113]
Cardiac Segmentation	U-Net/self-supervised		[114]
Bladder Volume Estimation	Coarse-to-fine DL	Biomedical Diagnostics	[101,115]
Cancer Risk Assessment	Multimodal CNN		[116]
Thyroid Cancer Diagnosis	Explainable multimodal DL		[117]
Breast Cancer Fusion	HXM-Net + transfer learning		[118]
Crack Sizing (NDE)	Deep learning		[119]
Defect Detection (SHM)	ML/pattern recognition	Physiological & Wearable	[120]
Muscle State Estimation	ML classification		[121,122]
Wearable Echomyography	CNN (single transducer)		[123]
Continuous Blood Pressure	Demographic feature learning		[124,125]
Cardiac Hemodynamics	Deep learning		[126]
Finger/Hand Motion	Deep learning (forearm US)	Human-machine Interface	[94]
Blood Pressure	ML for BP estimation		[127]
Gesture Recognition	CNN/end-to-end DL		[128–130]
Air Writing	DNN	Edge & In-Sensor	[131]
VR Interaction	Deep learning		[132]
Lightweight Edge Inference	Lightweight CNN/SoC	Industrial & Environmental	[101]
In-Sensor/SoC Computing	CNN/USoP		[100]
Chemical Identification	Artificial neural network (ANN)	Industrial & Environmental	[133]
Bubble/Flow Recognition	ML classifier		[134,135]
Environmental Multi-Parameter	Signal processing + ML		[136]
Fluid Viscosity/Density	Physics-based + ML		[137]

Technology Maturity and Deployment Challenges

Compressed sensing techniques applied to bulk ultrasound have reached TRL 5–6 (system validation in relevant environments), while MUT-specific implementations remain at TRL 3–4 (proof of concept in lab). Deep unfolding networks for signal recovery are algorithmically mature at TRL 4–5, but their deployment on MUT arrays faces several hardware-imposed constraints.

The most immediate hardware constraint is data bandwidth: a 128×128 CMUT array sampled at 40 MHz with 12-bit resolution generates tera-bits per second of raw data, far exceeding the throughput of typical ASIC interconnects. Real-time compressed sensing and on-chip sub-sampling must therefore operate within a power budget of tens of milliwatts for portable devices, which currently limits achievable compression ratios and reconstruction quality. Latency poses an additional constraint, since real-time imaging demands sub-50 ms per frame, a target difficult to meet with iterative reconstruction algorithms; learned approaches offer single-pass inference but require specialized neural accelerators. Even when algorithms are available, transferring models trained on bulk ultrasound data to MUT signals is non-trivial due to differences in aperture geometry, element directivity, SNR, and bandwidth; a model trained on 128-channel clinical phased-array data may degrade significantly when applied to a 32-channel PMUT array with 30 dB lower per-channel SNR. Underlying all of these challenges is the scarcity of MUT-specific training data compared to the abundance of clinical ultrasound datasets, and generating representative training sets requires extensive FEM simulation or experimental campaigns.

4.2. Image Enhancement and Super-Resolution

The intrinsic noise and low contrast of raw ultrasound signals, often exacerbated by the miniaturized nature of micromachined transducers, necessitate advanced enhancement techniques. Generative Adversarial Networks (GANs) are utilized to synthesize ultrasound training data and augment sparse datasets. For instance, frameworks like 2S-BUSGAN utilize a two-stage approach to generate annotated breast ultrasound images with structural legitimacy, effectively overcoming data imbalance [99]. In the domain of super-resolution, context-aware deep learning pipelines such as LOCA-ULM enable the high-efficacy localization of high-concentration microbubbles [96]. By identifying microvascular features that are often undetected by conventional localization microscopy, these algorithms enable deep tissue imaging with significantly improved precision. The integration of virtual elastography synthesizing strain maps from conventional B-mode images via GANs further extends the diagnostic capability of portable devices to potentially narrow the gap with high-end clinical equipment [108] in specific tasks. Self-supervised learning has also shown promise in label-free segmentation for cardiac ultrasound [114], achieving clinical validity without the need for laborious manual annotations. These computational methods help extract maximum diagnostic value from limited signal sources, enhancing the performance of portable hardware; however, they remain bounded by the fundamental information content of the acquired signals and cannot fully substitute for the superior raw SNR and broader bandwidth of high-end ultrasonic systems.

Furthermore, for medical adoption, these computational methods must move beyond raw performance metrics toward interpretability. Future systems should integrate Explainable AI (XAI) frameworks that combine clinical data with ultrasound images to provide clinicians with interpretable insights such as highlighting the acoustic features driving a cancer diagnosis rather than producing opaque confidence scores. As exemplified by explainable multimodal deep learning models [117], the path toward clinical translation requires algorithms that earn trust through transparency.

Critical Limitations

The image enhancement algorithms reviewed above, while impressive in their demonstrated performance, share several common limitations when considered for MUT-based deployment. Most GAN-based enhancement and super-resolution methods have been validated on clinical bulk-ultrasound data with SNR values typically 10–20 dB higher than what a single PMUT channel can provide. The effectiveness of these methods degrades markedly as input SNR decreases, and below a certain threshold (approximately 0–5 dB per channel for many architectures), the enhancement becomes unreliable, with GANs potentially introducing hallucinated anatomical features that can mislead diagnosis. This is a critical safety concern for medical applications: generative models can produce visually convincing images from extremely degraded inputs, but the information content is upper-bounded by the input SNR regardless of algorithmic sophistication. Hardware constraints further complicate deployment. Deep super-resolution models often require GPU-class compute with inference latencies of seconds, whereas wearable MUT applications demand tens of ms latency and sub-100 mW power consumption. Lightweight architectures optimized for edge deployment are emerging [101], but they typically trade 5–10 dB in PSNR for a 10× reduction in multiply-accumulate operations, a trade-off that must be carefully evaluated for each application.

5. MUT-Integrated Intelligent Platforms and Systems

The integration of MUTs with AI algorithms has enabled active and intelligent perception, facilitating deployment in wearable healthcare, industrial monitoring, human-machine interaction (HMI), and beyond. This section presents several representative and innovative works wherein researchers integrate AI into MUT systems for applications across diverse fields.

5.1. Time-Domain Sensing Platforms

Time-domain sensing platforms typically utilize single-channel or small-array configurations to extract desired information from the amplitude, time-of-flight, frequency components, or raw waveform of ultrasound signals. Figure 5 presents typical intelligent MUT systems focusing on single-channel signal processing. For feature extraction, these systems often employ Convolutional Neural Networks (CNNs) or other architectures to process temporal data. For noisy signals, generative algorithms may be utilized to complement specific information.

Intelligent single-channel MUT systems

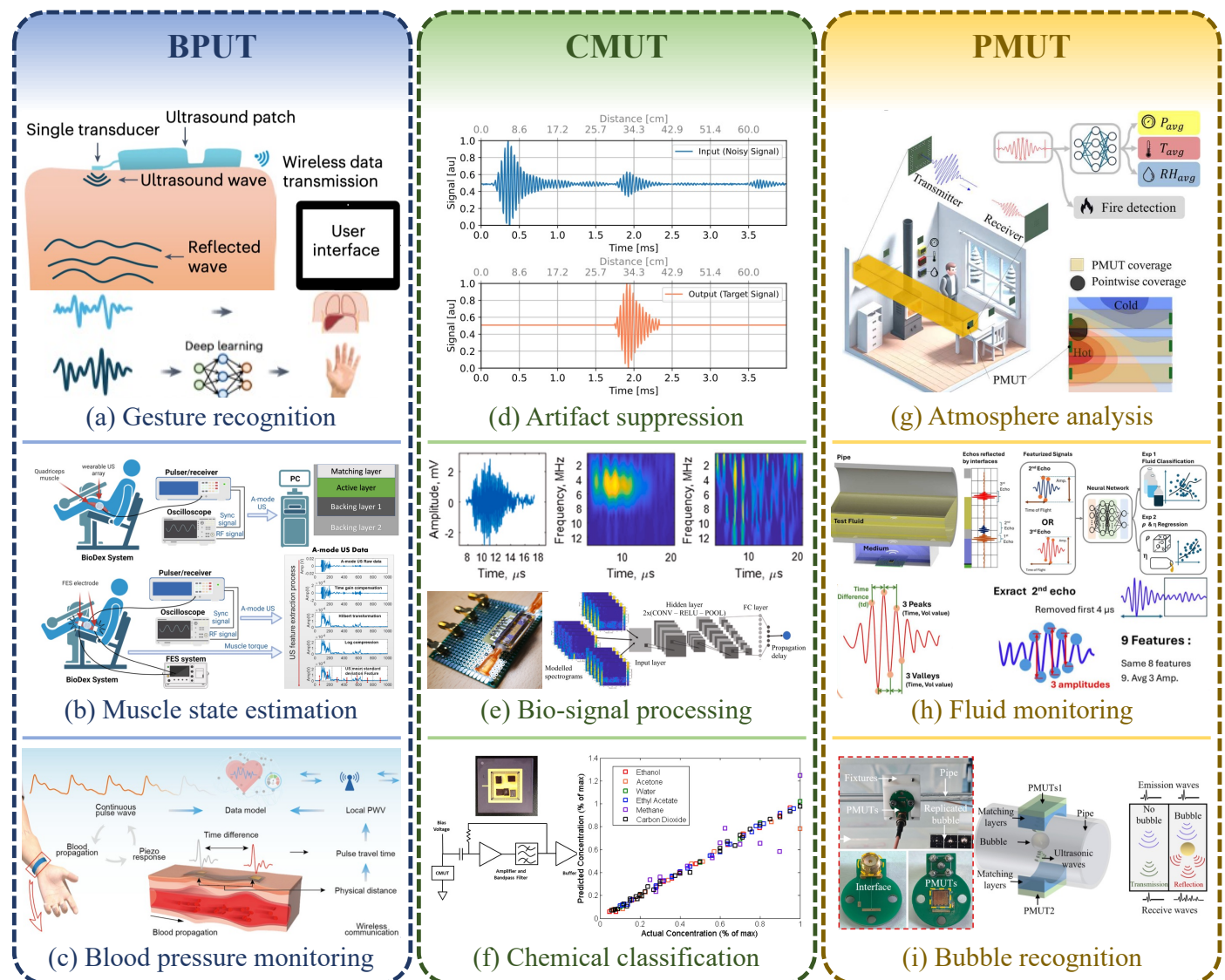


Figure 5. Intelligent MUT systems focusing on single-channel signal processing. (a) Wearable electromyography for muscular activity monitoring [123]. (b) ML-enhanced quadriceps muscle state estimation [121] ©2023 IEEE. (c) Continuous arterial blood pressure monitoring via flexible PMUT arrays [138]. (d) Deep learning-based artifact suppression for airborne MEMS transceivers [107] ©2023 IEEE. (e) CNN-enhanced SNR improvement in CMUT biosensors [97]. (f) Intelligent chemical identification using PMUT-based spectral analysis [133] ©2014 IEEE. (g) Multi-parameter environmental monitoring platform [136] ©2025 IEEE. (h) Contactless fluid viscosity and density characterization [137] ©2025 IEEE. (i) Noninvasive bubble recognition for industrial pipe monitoring [134] ©2025 IEEE.

In industrial non-destructive evaluation (NDE), accurately sizing internal defects remains challenging due to grain-induced scattering and signal attenuation. Recent work by Fei et al. demonstrated a deep learning-based diffraction data analysis method that automates crack sizing with high precision [119]. Similarly, in airborne applications, artifact suppression is critical for reliable distance estimation. Fusco et al. proposed a deep learning approach for MEMS-based airborne transceivers that effectively filters environmental interference, enhancing the robustness of contactless sensing [107]. Lee et al. proposed a plant dehydration monitor powered by generative artificial intelligence [139]. For fluidic environments, PMUT-based systems have been developed to recognize non-invasive bubble patterns in pipes [134] and monitor fluid viscosity and density without direct contact [137], highlighting the versatility of AI in interpreting complex acoustic–fluid interactions. Liquid viscosity detection based on harmonic engineering and dual-frequency PMUT arrays has further demonstrated the precision achievable in contactless fluidic characterization [140]. PMUT-based Doppler flowmeters have demonstrated real-time blood flow measurement capabilities with wearable form factors [141–144], extending single-channel platforms toward clinical diagnostics. Non-contact surface temperature sensing via bimorph PMUT arrays has also been demonstrated, expanding PMUT utility toward thermal monitoring [145].

In the biomedical domain, these novel smart platforms have advanced physiological monitoring. Wearable electromyography [123] or sonomyography [122] systems leveraging ultrasonic sensing provide detailed insights into muscular activity. Bimorph PMUTs have been applied to imaging of muscle-like phantoms, pointing toward wearable muscle disorder diagnostics [146]. Specifically, wearable A-mode ultrasound coupled with ML classification has been utilized for accurate quadriceps muscle state estimation [121]. These sonomyography systems outperform traditional surface EMG by capturing deep-tissue structural changes. Furthermore, ultra-thin flexible transducers have enabled continuous, non-invasive monitoring of arterial blood pressure waveforms [138]. Biological bone age assessment via PMUT systems has also been explored, demonstrating the potential of compact ultrasonic hardware for pediatric and orthopedic screening [147]. Radius of curvature measurement via PMUTs has been demonstrated as a method for surface profiling and structural inspection [148]. The intelligence of these platforms is further exemplified by the use of CNNs to significantly increase the SNR in CMUT-based biosensors [97] and facilitate accurate chemical identification [133]. For environmental applications, integrated multi-parameter environmental monitors now leverage such signal intelligence to simultaneously track temperature, humidity, and gas concentrations [136]. Battery status monitoring based on ultrasonic technology represents another emerging industrial application enabled by PMUT platforms [149].

5.2. Array-Based Imaging and Mapping Systems

Multi-dimensional spatial mapping necessitates integrated array systems capable of synchronous multi-channel data acquisition. Figure 6 presents typical intelligent MUT systems focusing on multi-channel signal processing and spatial mapping.

Intelligent multi-channel MUT systems

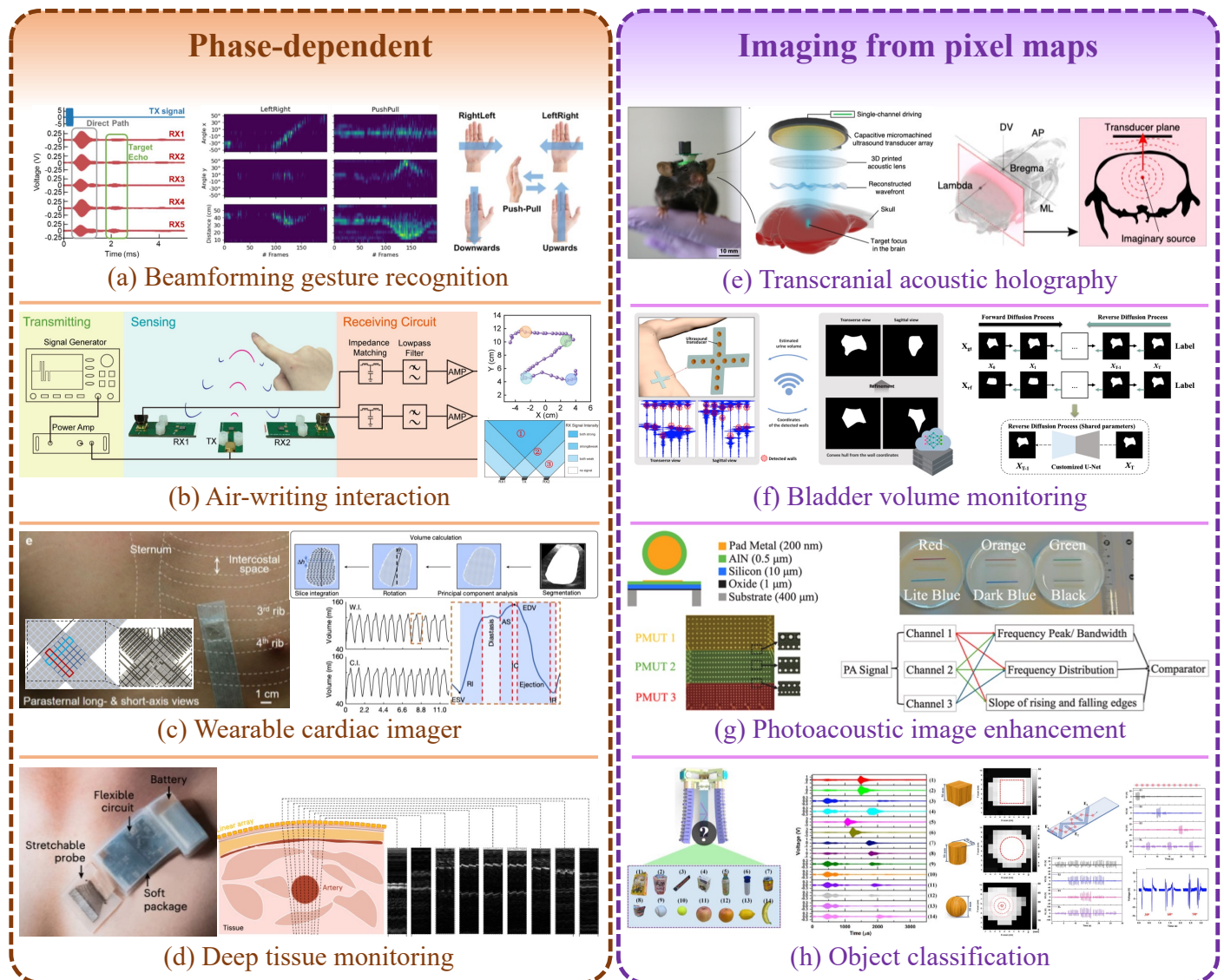


Figure 6. Intelligent MUT systems focusing on multi-channel signals and spatial mapping. (a) Gesture recognition via SNN-based beamforming [112] ©2022 IEEE. (b) Non-contact air writing for advanced HMI [131]. (c) Wearable cardiac ultrasound array for continuous hemodynamics [126]. (d) Deep tissue monitoring using fully integrated USoP platforms [100]. (e) Transcranial focused ultrasound for intelligent neuromodulation [150]. (f) Intelligent bladder volume monitoring via coarse-to-fine deep learning [115] ©2024 IEEE. (g) Multi-frequency color photoacoustic imaging [111]. (h) Intelligent soft robotic grippers with multimodal ultrasonic feedback [151] ©2023 IEEE.

These platforms often integrate AI-powered beamforming [98], where neural networks optimize the delay-and-sum process to reduce sidelobes and improve image contrast. In the realm of HMI, gesture recognition has seen recent advancement. Ultrasonic transducer arrays are utilized with ML to achieve high-accuracy hand gesture recognition, overcoming the lighting limitations of optical cameras [128–130]. More advanced operations such as air writing interfaces now enable non-contact HMI [131], while spike-based beamforming using neuromorphic SNNs has been proposed to minimize the computational overhead of real-time gesture tracking [112]. Haptic feedback via PMUTs represents a complementary modality for HMI, enabling ultrasound-induced tactile sensations and auto-positioning haptic stimulation [152,153]. Multimodal normal and shear force tactile sensing via PMUTs has further expanded the range of interaction cues available to robotic and HMI systems [154].

While HMI often targets human body objects in air, ultrasonic medical imaging faces more complex and noisy environments wherein target objects exhibit subtle features for diagnosis or monitoring. Wearable monitoring systems integrated with MUT arrays and advanced algorithms have been developed [127,155,156]. More integrated and miniaturized medical imaging systems represent the most complex application of array-based MUT systems [157–159]. Wearable cardiac ultrasound imagers now enable real-time monitoring of heart function during daily activities [126]. Stretchable ultrasonic phased arrays have been demonstrated for continuous monitoring of deep-tissue hemodynamics, enabling real-time measurement of blood flow velocity and arterial diameter in moving subjects [160]. High fill-factor rectangular PMUT phased arrays have been designed to achieve high sound pressure output for high-quality imaging, while pulse-echo imaging with AlN PMUT arrays using transmit beamforming has enabled short-range, high-resolution ultrasound [161–163]. Two-dimensional ultrasound imaging using a single transducer pixel based on spatial-spectrum correlation has been explored as a path to further miniaturize imaging systems [164]. Stretchable ultrasonic arrays for 3D mapping of deep tissue modulus have extended the capabilities of wearable platforms beyond imaging toward quantitative elastography [165]. Transcranial-focused ultrasound systems integrated with multifocal neuromodulation algorithms represent the cutting edge of non-invasive brain therapy [150], while conformal ultrasound patches have also enabled transcranial volumetric imaging of the brain [166]. For deep tissue monitoring in moving subjects, fully integrated Ultrasound-on-Chip (USoP) systems utilize CNNs to track arterial pulsations and maintain focus despite motion artifacts [100]. Intelligent bladder volume monitors have also been developed, employing a coarse-to-fine ML strategy that combines local feature extraction with server-side refinement to achieve clinical-grade accuracy [115]. Beyond bulk ultrasound, PMUT-based photoacoustic [109] or thermoacoustic [167] imaging has benefited from deep learning-based image quality enhancement. Wearable photoacoustic patches have further enabled simultaneous three-dimensional mapping of hemoglobin concentration and core temperature [168]. Miniature photoacoustic sensing systems integrating advanced PMUTs and vertical-cavity surface-emitting lasers (VCSELs) have demonstrated compact and sensitive photoacoustic detection [169–171]. High-frequency PMUT arrays have been explored for intravascular ultrasound imaging, demonstrating the potential for catheter-based diagnostic imaging [172]. Waveguide PMUT arrays have also been applied to short-range pulse-echo imaging [173]. Miniature wireless ultrasonic imaging systems for wearable carotid artery health monitoring represent a step toward fully autonomous cardiovascular screening [174].

Industrial applications include fluid detection or monitoring [135]. Surface condition sensing using broadband and highly directional PMUT arrays has demonstrated the ability to distinguish between liquid and ice surface layers with high accuracy [175,176]. Real-time differential ultrasonic flow sensing enabled by PMUT phased arrays with a novel V-shaped beam pattern has achieved precise flow measurement [177]. Underwater ultrasound communication based on PMUTs with DC bias voltage tuning has demonstrated the versatility of PMUT platforms for subsea data links [178]. In robotics and environmental reconstruction, ultrasonic arrays provide a robust alternative to LiDAR. Ohara et al. demonstrated 3D object reconstruction in outdoor environments using an ultrasonic image array coupled with a variational autoencoder (VAE), enabling the system to reconstruct object shapes despite high environmental noise [113]. The trend in multi-channel systems is toward integrated perception, wherein the MUT array and the AI backend are co-optimized to reconstruct reality from acoustic reflections.

5.3. Multi-Sensor Fusion Systems

Beyond transducer array-based systems, approaches involving multiple transducers and fusion algorithms have emerged as a more advanced framework across various domains. The sensor fusion section is organized into five categories based on the type of sensor modalities fused with ultrasound: (1) Ultrasound–ultrasound fusion, combining multiple ultrasonic signals for improved imaging; (2) Ultrasound + physiological sensors, integrating ultrasound with bio-signals such as EMG, IMU, and pressure; (3) Ultrasound + optical modalities, co-registering ultrasound with light-based imaging; (4) Ultrasound + robotic perception sensors, fusing acoustics with navigation and tactile sensors; and (5) Ultrasound + industrial sensors, combining ultrasonics with thermal, dielectric, and flow measurements.

1. Ultrasound–Ultrasound Fusion

Basic methods include fusion of images from different transducers or modes [179] to enhance the performance of ultrasonic imaging systems. In clinical oncology, deep learning models integrate multiview ultrasound images to prospectively assess breast cancer risk and reduce manual subjectivity [116], while hybrid architectures like HXM-Net fuse B-mode and Doppler data to achieve diagnostic accuracies of up to 94.20% [118]. Industrial applications have similarly leveraged ultrasonic fusion for high-resolution temperature tracking [180] and flow rate measurement in partially filled pipes [181], alongside advanced methods such as improved Dempster-Shafer evidence theory for fusing multi-harmonic nonlinear responses to identify micro-crack groups with 95.68% accuracy [182]. In these MUT-relevant fusion architectures, the complementary information arises from the fact that different ultrasonic modes (B-mode, Doppler, harmonics) probe different physical properties that together provide a more complete material or tissue characterization from a single, compact transducer platform.

2. Ultrasound + Physiological Sensors

In the domain of HMI and physiological monitoring, fused platforms exploit the depth-penetrating, noise-immune nature of ultrasound to enhance performance in ecologically valid environments. Yin et al. explored neuroprosthetic control by fusing A-mode ultrasound morphology with surface EMG (sEMG) and inertial measurement units (IMU), achieving classification accuracies up to 96.9% for amputees through a hierarchical control strategy [183,184]. A key advantage of MUTs in this context is their compact form factor and low power consumption, enabling integration into wearable patches that would be impractical with bulk transducers. Ultrasound here uniquely provides depth-resolved structural information from subcutaneous tissues up to several centimeters that surface EMG and IMU cannot access, while EMG and IMU contribute surface-level neuromuscular timing and limb orientation data, making the fusion synergistic for ambulatory monitoring. For advanced behavioral recognition, Yao et al. integrated 77 GHz mmWave radar with a 40 kHz ultrasonic array using an Attention-CNN-BiLSTM architecture, exploiting the complementary range and penetration characteristics of both modalities to reach an accuracy of 98.6% [185]. Other wearable innovations include conformal microsystems for cuffless blood pressure monitoring using ultrasound + pulse wave pressure [124], demographic-adaptive evaluations of radial artery stiffness [186], and the integration of ultrasonic ranging with low-resolution infrared arrays for edge-based fall detection [187,188]. Subcutaneous PMUT implants have extended continuous blood pressure monitoring to ambulatory large-animal models, pointing toward fully implantable cardiovascular sensors [189].

3. Ultrasound + Optical Modalities

Co-registering ultrasonic and optical modalities leverages the deep-tissue penetration of acoustic waves alongside the high spatial resolution and molecular specificity of optical interrogation. Explainable multimodal deep learning frameworks [117] now combine standard B-mode ultrasound with clinical data to predict complex outcomes such as thyroid cancer lymph node metastasis. Transparent ultrasound transducers (TUTs) allow seamless fusion of ultrasound imaging (USI) with photoacoustic imaging (PAI), optical coherence tomography (OCT), and fluorescence imaging (FLI) [190]. This quadruple fusion method provides an SNR 11 dB higher than commercial alternatives, enabling detailed characterization of vascular morphology and tissue stiffness. The contribution of ultrasound is its ability to image through optically scattering or opaque tissue at depths of centimeters, while optical modalities provide sub-surface resolution (<1 mm) and molecular specificity that ultrasound lacks, which is a combination particularly valuable for MUT-enabled miniaturized probes where footprint constraints preclude large-aperture optics. Clinical interventions have increasingly relied on volume navigation, where live ultrasound images are co-registered with pre-procedure CT or MRI data using magnetic trackers [191–193]. Such systems have been validated for guiding liver ablation, prostate biopsies [194], and prenatal diagnosis [195]. The fusion of transverse ultrasound images with multicore optical shape sensors has been utilized to track magnetically actuated catheters, where Kalman and Luenberger state estimators achieved a tip tracking error of only 0.085 mm [196].

4. Ultrasound + Robotic Perception Sensors

Multi-modal platforms leveraging MUTs enhance robotic perception and autonomous navigation in complex or light-constrained environments. Ultrasound complements LiDAR, cameras, and radar by detecting transparent obstacles and measuring reliably in direct sunlight or complete darkness, where optical sensors may fail. In mobile robotics, ultrasonic transducers are frequently fused with LiDAR, depth cameras, and PIR sensors to detect transparent obstacles and manage negative obstacles such as drop-offs [197,198]. These systems often utilize Bayesian filters and occupancy grid mapping to combine sparse ultrasonic measurements with high-resolution visual data [199]. Other specialized platforms include autonomous soft robotic systems with multi-modal sensors for self-adaptive manipulation [200], advanced pedestrian detection systems for adverse weather safety [201], and 3D surface mapping frameworks that compensate for hydrodynamic distortions in airborne sonar [202]. To ensure reliability, these platforms integrate global data from GPS and compasses with local perception from laser and ultrasonic sensors [203,204].

5. Ultrasound + Industrial Sensors

In industrial process monitoring and structural health evaluation, fusion strategies have evolved from simple linear models to complex deep learning frameworks. Ultrasound provides volumetric penetration and internal defect detection capabilities that surface-level industrial sensors like thermal or dielectric cannot offer, while those sensors provide complementary near-surface process context. Abu-Zahra demonstrated a foundational fusion strategy using a Multi-Layer Perceptron to integrate ultrasonic acoustic impedance and sound velocity with dielectric permittivity measurements for polymer melt monitoring, achieving correlation coefficients of 0.96 and 0.92 for density and viscosity [205]. Zamiela et al. proposed a multi-modal U-Net architecture to fuse in-situ thermal history with ex-situ volumetric ultrasonic data for porosity detection in laser-based additive manufacturing, achieving a mean Intersection over Union (mIoU) of 0.93 [206]. PMUT-based bone conduction systems have been integrated with air-conduction data via attentional feature fusion (AFF) and deep complex convolutional recurrent networks (DCCRN), reducing character error rates by over 20% in speech vibration capture [207]. To manage

the substantial computational load, intelligent wavelet-based pre-filtering and refinement algorithms have been developed to optimize system runtime by up to 98.5% [208,209].

Table 4 summarizes the sensor fusion applications mentioned above.

Table 4. Typical sensor fusion applications involving ultrasonic signals.

Domain	Sensors	Fusion Level	Method/Architecture	Ref.
Consumer	PMUT + IMU/sEMG/Mic	Feature	RNN/LSTM/AFF/DCCRN	[207,210–212]
Automotive	UT + LiDAR/Camera/GPS/etc.	Decision	GASF/LOP/K-Means/YOLO	[197–199,201,203,204]
Industrial	UT + Dielectric	Data	MLP + ANN	[205]
Industrial	UT + Thermal	Feature	Two-branch U-Net + LSTM	[206]
Industrial	UT + HB-TENG + Pressure	Feature	GASF	[200]
Industrial	Multiple UTs	Decision	Weighted DS + CNN/etc.	[180–182]
Industrial	Sonar + Optical	Data	Image Fusion	[202]
Medical	UT(A-Mode) + sEMG + IMU	Feature	DLA + PCA	[183]
Medical	UT(2D) + FBG Optical	Decision	Luenberger & Kalman Est.	[196]
Medical	UT(B-Mode) + RF	Data	CAF + U-Net/CE-Net	[213]
Medical	UT + CT/MRI/Thermal	Data	Image Fusion	[191–193,195,214]
Medical	Transparent UT	Data	Image Fusion	[215]
Medical	UT(B-Mode) + UT(Doppler)	Feature	HXM-Net + Transfer Learn.	[118]
Medical	UT + sEMG	Feature	CNN-LSTM	[184]
Medical	PMUT + Pressure	Data	Young’s Modulus	[186]
Medical	IVUS + Magnetic	Data	GVF Snake	[216]
Medical	Transparent UT + OCT + FL	Data	Image Fusion	[190]
Healthcare	PMUT (ToF) + IR	Decision	CUSUM + RFA	[187]
Healthcare	UT + RADAR (mm-Wave)	Feature	Attention-CNN-BiLSTM	[185]
Healthcare	UT + PWF (Pressure)	Feature	Demographic Feature Learn.	[124]
Healthcare	UT + IMU	Feature	IOAM/CNN/etc.	[188,217,218]
/	UT Array	Data	Wavelet-based Optimization	[208,209]

5.4. Edge Intelligence and In-Sensor Computing

To address power consumption bottlenecks and minimize wiring noise in real-time AI inference, the next frontier for intelligent micromachined transducers lies in realizing in-sensor computing. Lightweight CNNs optimized for SoC architectures enable real-time applications such as wearable bladder volume measurement, operating at high frame rates with minimal power consumption [101]. Such edge computing approaches are supported by the broader advancement of ML in ultrasonic NDE and SHM, where advanced data mining and pattern recognition are used to decode intricate defect patterns in real time [120]. The deployment of these algorithms on resource-constrained hardware will be critical for the broader advancement of ML in SHM and autonomous diagnostic systems, where the transducer itself becomes the primary node for data refinement. These integrated

systems, where signal processing occurs at the sensor rather than in the cloud, represent the culmination of the convergence between MUT hardware and AI software.

A defining advantage of MUTs over bulk transducers is their CMOS compatibility, which enables monolithic integration of transduction elements with readout and processing circuits. Front-end interface circuits typically include low-noise amplifiers (LNAs) for receive channels, transimpedance amplifiers (TIAs) for CMUT current sensing, and high-voltage drivers for transmit pulsing. PMUT-specific drive circuits often leverage charge-recycling or switched-capacitor topologies to minimize power consumption in battery-operated wearable systems. For CMUTs, the high DC bias voltage places stringent requirements on isolation and protection circuitry, and on-chip charge-pump or DC-DC converters are commonly implemented to generate the bias from a low supply voltage. Multiplexing and channel-reduction strategies including row-column addressing and micro-beamforming are critical for managing the 10^2 – 10^4 elements in 2D arrays within the pin-count constraints of ASICs. On-chip analog-to-digital converters (ADCs) with moderate resolution (10–14 bit) and sampling rates (10–80 MHz per channel) are integrated to digitize received echoes before beamforming. Emerging beamforming ASICs incorporate digital delay-and-sum engines for real-time image formation, while advanced designs are beginning to embed lightweight neural network accelerators for edge AI inference directly on the same die or in the same package. Power-management circuits and wireless communication modules (Bluetooth Low Energy, ultra-wideband, or near-field data links) complete the system, enabling fully autonomous wearable or implantable ultrasonic devices.

Packaging is a critical determinant of MUT performance that warrants dedicated attention, particularly for wearable, implantable, and industrial deployments. Acoustic matching and backing layers must be carefully engineered to maximize energy transfer into the target medium while minimizing internal reflections. Encapsulation materials for implantable MUTs require biocompatibility and long-term chemical stability in physiological environments. Waterproofing is essential for both wearable sweat-tolerant patches and underwater or pipeline inspection systems, typically achieved through parylene-C or silicone encapsulation. Flexible interconnects using polyimide, liquid-crystal polymer (LCP), or stretchable metal traces are needed to connect rigid MUT dies to flexible system boards without fatigue failure under repeated bending. Mechanical fatigue from continuous vibration and thermal drift from body-temperature fluctuations must be modeled and mitigated at the system level. Operation in air versus liquid versus tissue presents fundamentally different acoustic loading conditions that affect membrane displacement, bandwidth, and reliability. Sterilization compatibility (ethylene oxide, gamma radiation, or autoclave) further constrains material choices for clinical-grade devices. These packaging and reliability factors must be addressed from the earliest design stages to ensure successful translation from benchtop prototypes to deployed systems.

6. Future Outlook and Conclusions

6.1. Open Challenges and Research Directions

Despite the rapid advancement of AI-augmented MUT systems, several technical and systemic challenges remain to be addressed for widespread clinical and industrial adoption. Below we outline concrete research directions organized around milestones that the community should prioritize.

6.1.1. Establishment of Public MUT Datasets

The efficacy of AI-powered inverse design and signal intelligence is fundamentally limited by the availability of high-quality, annotated datasets. While GANs provide a partial solution through data augmentation, the field would benefit greatly from community-

wide benchmarking datasets of MUT array signals with ground-truth labels for common tasks. The diversity of MUT configurations including frequency, array size, and specific application makes cross-study comparison difficult. The community would benefit from standardized phantom-based benchmarks for resolution, contrast, penetration depth, and frame rate, analogous to the ultrasound quality assurance phantoms used in clinical practice. Without such datasets, the reproducibility and comparative evaluation of AI algorithms across different research groups will remain challenging.

6.1.2. Physics-Informed and Uncertainty-Aware AI

PINNs already demonstrate that embedding governing equations into neural network training improves generalization with limited data. Future architectures must incorporate stochastic modeling to quantify prediction variances, establishing confidence boundaries for safety-critical clinical applications. This is critical for safety-sensitive applications such as implantable monitoring and surgical guidance, where overconfident but incorrect predictions could lead to clinical harm.

6.1.3. Edge-AI ASICs Co-Designed with MUT Arrays

The co-design of custom ASICs that integrate neural network accelerators directly with MUT readout circuits represents a promising direction. Such chips would enable real-time, low-latency AI inference at the sensor node without offloading data to external processors, addressing the bandwidth and power bottlenecks identified in previous sections. Early stage co-design, where transducer geometry and neural network architecture are jointly optimized, could yield substantially improved system-level efficiency.

6.1.4. Synthetic Training Data for Sparse-Data Regimes

In many MUT applications, including NDE of rare defect types or monitoring of uncommon physiological conditions, the availability of labeled training data is extremely limited. An important future direction is the generation and validation of synthetic acoustic signals for training neural networks, using physics-based simulation engines to produce diverse, labeled datasets that capture the relevant acoustic propagation physics. This approach, already adopted in the broader NDE community for training defect-classification models, should be extended to MUT-specific applications, particularly for optimizing transducer designs under insufficient experimental data.

6.1.5. Dynamic Sensor Reconfiguration via AI

Improving one transducer parameter during design often leads to deterioration in another. Beyond multi-objective optimization of static designs, an emerging research direction is the use of neural networks to dynamically reconfigure a single sensor for multiple distinct sensing tasks. For example, a PMUT array could be reconfigured through AI-driven voltage biasing and sub-array selection to switch between high-resolution imaging mode, wide-field monitoring mode, and Doppler flow measurement mode, adapting its acoustic characteristics in real time to the task at hand. This concept of task-adaptive reconfiguration extends the role of AI beyond design and signal processing into the operational control layer of intelligent ultrasonic systems.

6.1.6. Closing the Design–Processing Loop

As discussed above, the closed-loop coupling between AI-driven inverse design and AI-driven signal processing has not yet been demonstrated in a single fabricated system. This represents both a critical research gap and a high-value target: a complete workflow where a freeform MUT geometry is discovered by AI inverse design, fabricated with PDK-compliant constraints, and its non-intuitive acoustic response is subsequently interpreted

by a complementary AI signal-processing pipeline. Verifying this closed-loop relationship experimentally would validate one of the central hypotheses of the field.

6.1.7. Calibration and Fabrication Robustness

MEMS-based transducers are inherently sensitive to manufacturing tolerances and environmental fluctuations. Traditional calibration methods are often insufficient for the dynamic conditions encountered in wearable applications. The gap between simulation-predicted and as-fabricated performance remains a critical challenge: while DRL-generated freeform shapes and AI-optimized designs are promising in simulation, the next step is to verify these designs against actual PDK constraints and fabrication realities, ensuring that performance predicted *in silico* translates reliably to physical devices. Self-calibrating architectures that leverage embedded reference elements or multi-modal cross-validation represent a more principled path forward than purely data-driven approaches to fabrication offset compensation.

6.2. Conclusions

In conclusion, the integration of micromachined ultrasonic transducers and machine learning frameworks shifts ultrasound system design from deterministic structural optimization toward adaptive, hardware–software co-designed platforms. By combining the low-impedance, CMOS-compatible hardware of PMUTs and CMUTs with the predictive power of ML, we are moving toward systems that can recover latent information from noisy or sparse measurements, adapt to changing environments, and reduce hardware complexity at the system level. A realistic assessment must acknowledge the boundary between what algorithmic intelligence can and cannot achieve: ML methods excel at extracting weak or corrupted signals from noisy measurements, yet they remain fundamentally bounded by the information content captured at the transducer level. No amount of post-processing can compensate for acoustic energy that was never received, nor can any algorithm circumvent the thermodynamic noise floor or the diffraction limit of a finite aperture. As design methodologies transition toward autonomous inverse design, and platforms embrace multi-modal sensor fusion and task-adaptive reconfiguration, system integration will continue to evolve, leading to practical and deployable intelligent ultrasonic interfaces.

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