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Weaving Intelligence: Thermally Drawn Multimaterial Fibers Toward AI-Enabled Smart Textiles

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ABSTRACT

The rapid evolution of smart textiles is intensifying demand for multimaterial systems that couple mechanical compliance with embedded, adaptive computational capabilities. Thermally drawn fibers have emerged as a powerful platform, enabling the co-integration of polymers, metals, semiconductors, and piezoelectric or iontronic phases into continuous multimaterial architectures with high geometric fidelity and manufacturing scalability. These hybrid fibers enable distributed sensing, energy modulation, and signal transduction, while generating high-dimensional data streams well suited for artificial intelligence (AI)-driven analysis. This review surveys recent advances at the intersection of AI and thermal drawing technologies, including data-centric optimization, real-time process control, signal processing, and predictive modeling, which are reshaping both fiber fabrication and system-level integration. We highlight progress in multimaterial co-drawing, hierarchical fiber engineering, and functionally integrated architectures that establish the foundation for in-fiber computation. Emphasis is placed on neuromorphic and spiking neural network (SNN)-based approaches, which enable energy-efficient, event-driven computation aligned with the distributed and deformable nature of textile platforms. Finally, we discuss emerging challenges and opportunities, including scalable neuromorphic architectures, uncertainty-aware learning, and AI-driven materials optimization. Together, these advances outline a pathway toward autonomous, self-optimizing textile systems in which individual fibers function as distributed, cognitively inspired nodes within next-generation intelligent materials.

1 | Introduction

The evolution of electronics from rigid, planar devices to soft, flexible, and stretchable systems is revolutionizing how technology interacts with the human body and environment. Advances in materials science, mechanics, and device architecture have

enabled applications ranging from implantable medical sensors and neural probes [1] to wearable biosensors [2], soft robotics [3], diagnostic and surgical tools [4], light-emitting devices [5, 6], and energy-harvesting textiles [7–10]. Among these, fiber-shaped electronics stand out for their flexibility, high aspect ratio, and compatibility with weaving and wearing. However,

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conventional microfabrication techniques, such as photolithography or nanoimprinting, are poorly suited to fibers' curved geometries. To overcome this, diverse fabrication methods including coating [11, 12], vapor deposition [13], physical convolution and wrapping [14], electrospinning [15], printing [16], and patterning techniques [17] have been explored, yielding coaxial, twisted, and interlaced fiber structures. Despite extensive progress, most conventional fabrication approaches for fiber-based electronics remain complex, low-yield, and difficult to scale, often requiring multiple processing steps and suffering from nonuniform performance along the fiber length [18]. Critically, fibers produced by these methods are typically composed of a single material, which restricts their ability to incorporate diverse functionalities and limits their use as stand-alone devices. The introduction of thermal drawing of multimaterial fibers has fundamentally transformed this landscape, offering a scalable, high-precision, and continuous route for integrating optical, electronic, and magnetic thermal or biological functionalities within a single fiber strand [19, 20]. By thermally scaling macroscopic multimaterial preforms into kilometer-long micro-structured fibers, this process enables precise control over geometry and material composition while maintaining structural uniformity [21]. Moreover, the fiber itself functions as an active materials platform, enabling the formation of novel phases, asymmetric micro-/nanostructures, and fully integrated device architectures [22]. These capabilities, unattainable through conventional fiber-processing methods, pave the way for next-generation textiles endowed with vision, hearing, speech, multimodal sensing, communication, energy harvesting and storage, as well as embedded data storage and computation (Figure 1a) [23, 24].

In parallel, the textile industry is experiencing a paradigm shift toward digitalization, propelled by automation, data-driven manufacturing, and the growing convergence of electronics with wearable systems [25]. Formerly confined to providing mechanical protection and comfort, conventional fabrics are now evolving into intelligent textile systems that integrate mechanical flexibility, softness, and embedded electronic functionalities. The global smart textile market, projected to expand from 2.98 billion USD in 2022 to over 8.5 billion USD by 2028 [25], is driving advances in biomedical monitoring, physical rehabilitation, and human-machine interfacing. Representative applications include textile-integrated biosensors for real-time physiological monitoring, wound-healing assessment, and electrocardiogram (ECG) signal acquisition [26], which enable continuous and unobtrusive health tracking [27]. The COVID-19 pandemic further accelerated research in smart personal protective equipment [28], leading to the development of sensor-embedded face masks capable of tracking respiration rate [29], environmental exposure [30], and infection-related biomarkers [31]. Within this rapidly evolving context, thermally drawn fibers have emerged as a credible candidate as a backbone for the next-generation of intelligent and responsive fabrics [32]. When interwoven into textiles, these fibers act as distributed multimodal nodes capable of real-time sensing, actuation, communication, and localized computation, thereby transforming traditional fabrics into adaptive, self-aware systems that bridge the gap between materials science, electronics, and artificial intelligence (AI) [33]. At its core, AI seeks to emulate aspects of human cognition and decision-making through computational architectures. In an era increasingly dominated by big data, AI leverages machine

learning (ML) algorithms, particularly artificial neural networks (ANNs), to extract meaningful insights and predictive knowledge from large, multidimensional datasets with high speed and precision [34]. Over the past decade, AI has evolved beyond traditional ANNs into spiking neural networks (SNNs) and neuromorphic computing frameworks, which emulate the biological efficiency, temporal coding, and event-driven dynamics of the human brain [35]. These advanced paradigms not only enhance computational performance but also offer a bioinspired foundation for the development of intelligent materials, a direction increasingly influential across domains such as smart wearables, human-machine interfacing, and adaptive textiles [36]. Reflecting these ongoing developments in smart textiles, the evolution can be classified into three generations: 1) First-generation textiles involved minimal integration of electronic components, serving primarily as passive substrates; 2) Second-generation textiles adapted conventional textile fabrication by embedding conductive threads or printed circuits, enabling basic sensing or actuation; and 3) Third-generation intelligent textiles incorporate electronic, sensing, and computational functions directly into the fiber matrix (Figure 1b) [37], resulting in intrinsic, material-level intelligence [38]. In recent developments, ML is rapidly emerging as a transformative tool for optimizing the thermal drawing process, the foundational technique for fabricating multifunctional fibers [25]. Through data-driven modeling and predictive analytics, ML algorithms can dynamically regulate temperature gradients, melt viscosity, feed rate, and drawing tension, thereby enabling real-time defect detection, adaptive process control, and parameter self-optimization [39]. This integration shifts the thermal drawing technique from a conventional process into an intelligent, closed-loop manufacturing system capable of learning from operational feedback to enhance yield and reproducibility. At the same time, the technique is evolving beyond passive functional carriers to serve as physical substrates for AI computation. Looking ahead, the integration of memristive [40], ferroelectric [41, 42], or iontronic components [43, 44] into the fiber architecture could enable thermally drawn fibers to perform in-fiber data processing, dynamically modulate their conductance states, and exhibit spike-based learning behaviors analogous to those observed in SNNs. Such AI-integrated thermally drawn fibers enable distributed, low-power neuromorphic computation, bridging the gap between data sensing and intelligent response. When interwoven into fabrics, these fibers collectively operate as neuromorphic networks, capable of sensing, processing, and adaptive decision-making, marking a transition from individual fiber "neurons" to a cohesive fabric "brain" [45].

This review examines the integration of AI with the multimaterial thermal drawing paradigm toward the development of intelligent and adaptive material systems. The discussion begins with an overview of the fundamental principles and fabrication methodologies of multimaterial, multifunctional fibers, with particular emphasis on recent advances in multimaterial co-drawing, hierarchical structuring, and functional integration that enable increasingly complex fiber architectures. In parallel, the role of AI in enhancing and optimizing the thermal drawing process is introduced. Subsequently, the application of conventional ANN-based algorithms in fiber-based sensing systems is analyzed, representing the first major convergence between AI methodologies and multimaterial thermally drawn fibers (Section 3). Building on this foundation, Section 4 explores the emerging

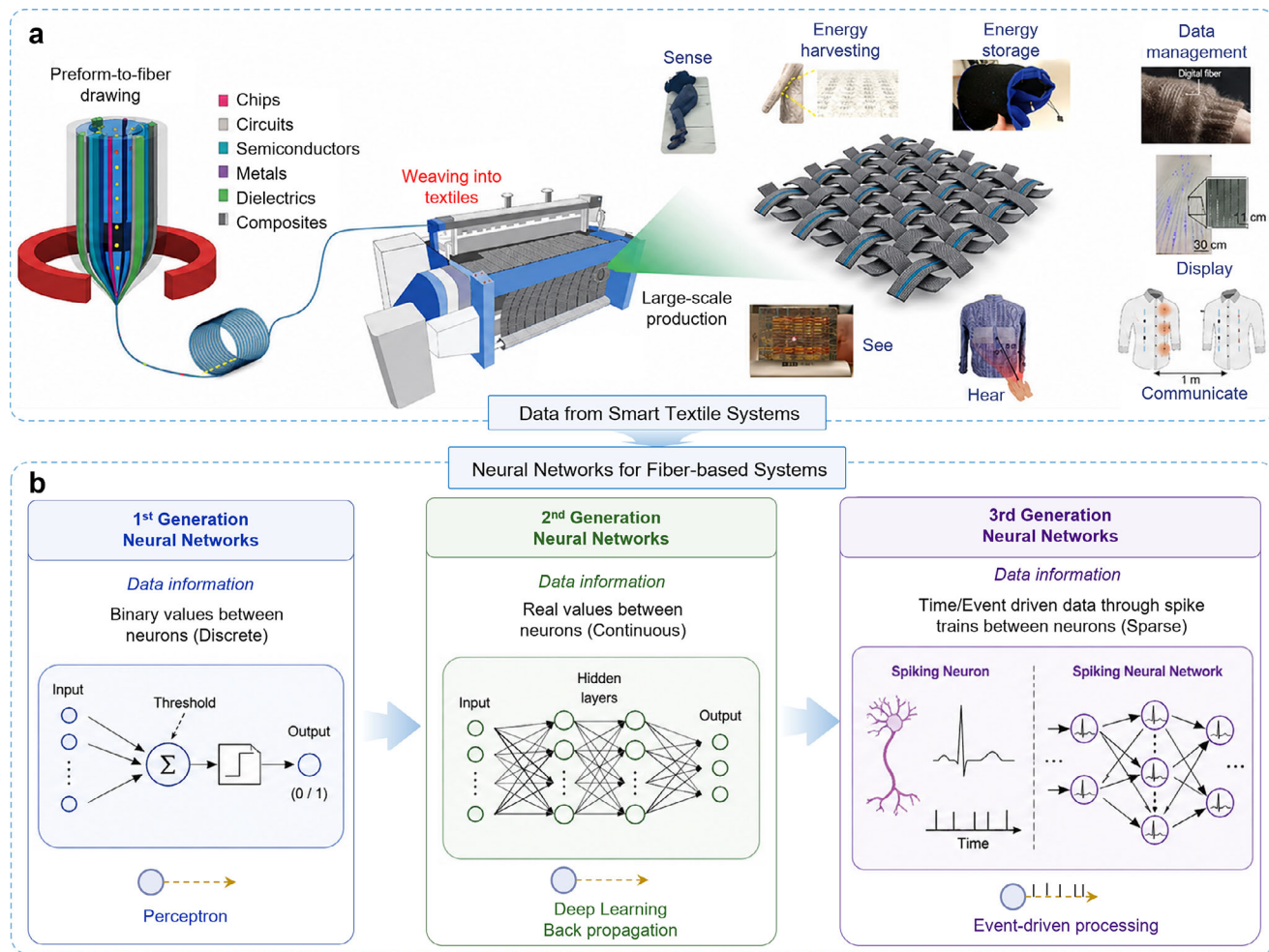


FIGURE 1 | Overview of the thermal drawing process and their convergence with next-generation neural network paradigms. (a) Thermally drawn fibers incorporating chips, circuits, semiconductors, metals, dielectrics, and composite structures can be directly woven into textiles, enabling a wide range of advanced functionalities. Reproduced with permission [4]. Copyright 2022, Springer Nature. Reproduced with permission [7]. Copyright 2020, Springer Nature. Reproduced with permission [23]. Copyright 2023, Oxford University Press. Reproduced with permission [46]. Copyright 2018, Springer Nature. Reproduced with permission [47]. Copyright 2021, Springer Nature. Reproduced with permission [48]. Copyright 2004, Springer Nature. Reproduced with permission [49]. Copyright 2020, Wiley-VCH. Reproduced with permission [50]. Copyright 2020, Wiley-VCH. (b) Core building blocks and emerging technologies shaping the next generation of fabric-AI-inspired future industry development trends.

incorporation of neuromorphic computing and SNN paradigms within fiber systems. SNNs are highlighted as a transformative pathway for fiber intelligence due to their event-driven operation, low-power consumption, and temporal adaptability, characteristics that are inherently compatible with distributed, fiber-scale environments. Within the next section, key challenges and future perspectives are discussed to position AI-embedded thermally drawn fibers as a reliable, scalable, and sustainable platform for intelligent textile systems. These challenges include material and structural design constraints, energy efficiency and adaptive operation, the development of neuromorphic fiber architectures, and the need for uncertainty-aware modeling to ensure robust performance under real-world conditions. This review aims to provide a comprehensive perspective on AI integration in such fiber platforms, while establishing a conceptual foundation for advancing fiber- and textile-based architectures toward next-generation, high-functionality wearable and interactive systems.

2 | Fundamentals of Thermal Drawing Process and AI Integration

2.1 | Top-Down Microfabrication via Shape-Preservation in Thermally Drawn Multimaterial Fibers

The thermal drawing process, originally developed for optical fiber fabrication [51], has evolved into a versatile technique for producing multifunctional, kilometer-scale fibers (Figure 2a,b). Its precise control over geometry and internal architecture enables the seamless integration of multiple materials and functional devices within a single continuous strand. Unlike conventional fiber fabrication methods, thermal drawing allows rapid, scalable, and automated production, making it particularly suited for smart textile manufacturing [52]. Today, the same principle that revolutionized optical communication is being extended to create multimaterial composite fibers combining

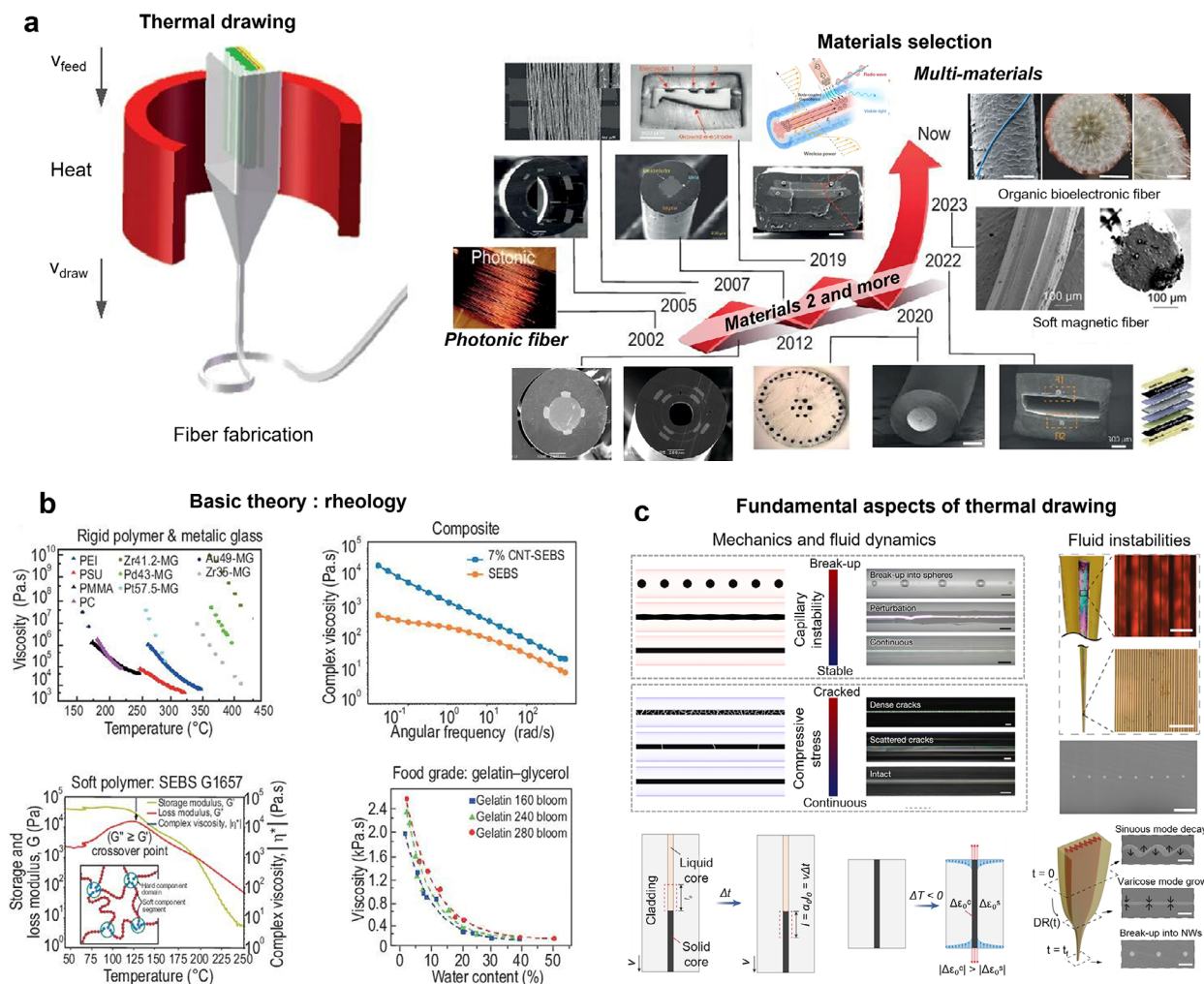


FIGURE 2 | Fundamental principles and material foundations underlying the thermal-drawing process. (a) Schematic of the thermal drawing process and the evolution of material selection, illustrating the transition from conventional optical-fiber materials to diverse multimaterial systems with increasing structural and functional complexity. (b) Rheological characteristics of representative rigid, soft, composite, and gel-based materials, emphasizing viscosity and viscoelastic matching as key criteria for stable multimaterial co-drawing. (c) Core mechanical and fluid-dynamic mechanisms during thermal drawing, including capillary stability, stress-induced deformation and cracking, and fluid instabilities that govern fiber morphology and micro/nanostructure formation. Reproduced with permission [1]. Copyright 2023, Wiley-VCH. Reproduced with permission [3]. Copyright 2023, Wiley-VCH. Reproduced with permission [8]. Copyright 2024, AAAS. Reproduced with permission [20]. Copyright 2020, Elsevier. Reproduced with permission [66]. Copyright 2024, Springer Nature. Reproduced with permission [83]. Copyright 2019, AAAS. Reproduced with permission [98]. Copyright 2024, Oxford University Press. Reproduced with permission [101]. Copyright 2022, Springer Nature. Reproduced with permission [113]. Copyright 2024, Springer Nature. Reproduced with permission [114]. Copyright 2024, Springer Nature.

electronic, photonic, and thermal functionalities, forming the foundation for next-generation intelligent and fabric-compatible systems [53].

In a typical thermal drawing process, a macroscopic preform, a cylindrical assembly containing all the desired materials and internal structures, is heated inside a drawing furnace to a temperature above its softening or glass transition point [54, 55]. One end of the preform is fixed at the top of the drawing tower, while the lower portion is softened or melted in the hot zone. Once a stable viscous state is reached, the softened region is drawn downward under the pulling force of the capstans, transforming the preform into a continuous fiber. When the drawing reaches a steady state, a necking region forms, and due to mass preservation, the fiber radius (r_{fiber}) is scaled from the

preform radius ($r_{preform}$) with a drawn-down ratio controlled by the preform feeding speed (v_{feed}) and the fiber drawing speed (v_{draw}) [20, 54, 56–58]:

$$r_{fiber} = r_{preform} \sqrt{\frac{v_{feed}}{v_{draw}}}$$

Although the actual process is considerably more complex, with advanced models accounting for phenomena such as Plateau-Rayleigh break-up, thermal reflow, and in-fiber crystallization [57–60], this simplified relationship provides a basic guideline for controlling fiber geometry, if controlled well, the final fiber faithfully preserves the composition, geometry, and internal architecture of the preform at the microscopic level [52–54, 61–63]. As a consequence, sophisticated transverse geometries can be

designed, incorporating optical waveguides [64, 65], conductive channels [66], electrodes [67], and hollow microchannels [57], to realize multiple functionalities within a single fiber. From an industrial perspective, the thermal drawing process offers precise size control, axial uniformity, and scalability, enabling the production of kilometers of multifunctional fibers in an automated, continuous manner [20, 52, 63].

A fundamental advantage of the thermal drawing process lies in its unique capability to manufacture continuous, kilometer-long fibers with highly sophisticated transverse geometries [54, 56, 68]. Among these structural innovations, core-shell and multicore designs represent particularly transformative advantages for functional fibers [22, 53, 63, 69]. Coaxial or core-shell configurations allow active functional elements to be intimately encapsulated by protective or functional polymer claddings, establishing robust, well-defined interfaces that are essential for stable electronic and optoelectronic performance [64, 67, 70]. Furthermore, multicore architectures can be readily realized using iterative “stack-and-draw” techniques, wherein multiple functional elements are bundled into a secondary preform and repeatedly drawn [60, 71]. This iterative processing not only exponentially reduces the feature sizes of the embedded cores but also enables the creation of highly dense double-, triple-, or quadruple-core arrays [69, 72]. Ultimately, these multicore and multilayered configurations can mirror the hierarchical organization of biological neural circuits, providing a highly scalable and structurally versatile hardware platform for next-generation intelligent textiles [73–75].

2.2 | Material Selection Criteria for Cladding Materials

To ensure reliable fabrication, materials must exhibit compatible glass transition (T_g) or melting temperatures (T_m) so that the T_{draw} allows viscous flow without degradation [76, 77]. Matching Vicat softening temperature (T_{vs}), α , and η minimizes internal stresses, delamination, and cracking [78]. Optimal cladding viscosity (10^4 – 10^8 Pa·s) ensures stable elongation, while strong interfacial adhesion and wettability prevent microvoids during quenching [62]. Thus, amorphous claddings, such as glasses and thermoplastics such as polymethyl methacrylate (PMMA) and polycarbonate (PC) are preferred due to their optical transparency, isotropic mechanical response, stable thermal behavior, and biocompatibility [64]. These are the same cladding used in optical fibers. Beyond those conventional cladding materials, stretchable elastomers, including styrene-ethylene-butylene-styrene (SEBS), emerges as the cladding of choice for acoustic and mechanical sensing fibers because of their elasticity and rheological compatibility with the thermal drawing process [4, 77, 79]. Table 1 summarizes representative T_g , T_{vs} , and α values for common polymers successfully used as cladding materials.

2.3 | Materials for Fiber Core Integration

Recent advances in rheological modeling, microstructural analysis, and fluid dynamics have significantly deepened the scientific understanding of the thermal drawing process, enabling a wide range of materials with significantly different electrical, thermal,

and mechanical properties than those of the cladding to be integrated in the core of thermally drawing fibers [98]. This capability has unlocked extensive research efforts toward integrating diverse materials compatible with the thermal drawing process, including polymers, metals, semiconductors, and functional composites within a single fiber architecture (Figure 2a). This trend of incorporating increasingly complex materials and functionalities into continuous, flexible fibers is rapidly expanding, with growing interest from research groups worldwide. For instance, studies have elucidated the stress-induced chain alignment and phase transitions, for instance, the α -to- β transformation in P(VDF-TrFE) that enhances piezoelectric and ferroelectric properties, and developed methods to draw metallic glasses and biodegradable or food-grade polymers through refined viscosity and flow control [59, 77, 91, 99]. In parallel, material integration has evolved from early photonic and polymer-based fibers toward increasingly complex multimaterial systems incorporating conductors, semiconductors, and functional composites (Figure 2b) [24, 48, 66]. This transition reflects a broader trend toward application-driven fiber architectures with integrated functionalities such as sensing, actuation, and energy conversion.

Advanced hydrodynamic and nano-metallurgical modeling has enabled the stable drawing of semiconducting cores [100], while engineered capillary instabilities have been exploited to fabricate encapsulated nanowire arrays with tunable morphology (Figure 2c) [101]. These breakthroughs, supported by X-ray scattering, mechanical simulations, and nano-scale characterization, have clarified the origins of cracks, deformation, and filament formation during drawing, guiding the design of cladding materials with balanced viscosity, thermal expansion, and elasticity [98, 102]. Moreover, diffusion barriers and buffer layers are now commonly employed to suppress chemical interdiffusion between metals, semiconductors, and polymers, preserving compositional and electrical stability in multimaterial architectures [103]. Finally, novel post-processing functionalization strategies for post-drawn fibers, including bioactive coatings, stimuli-responsive composites, and embedded biochemical sensors, have opened promising opportunities in bioengineering and biomedical applications [104, 105].

To further expand the functional capabilities of thermally drawn fibers, the strategic development of composite materials has become a critical research frontier [56, 106]. While pristine polymers provide the necessary mechanical compliance and rheological stability for the drawing process, they often lack the intrinsic electrical, piezoelectric, or catalytic properties required for advanced device performance [60]. To overcome this, conductive polymer composites are frequently engineered by dispersing nanoscale fillers, such as carbon black, carbon nanotubes (CNTs), and carbon nanofibers (CNFs), into thermoplastic matrices [107, 108]. For example, incorporating CNFs into a polymer already loaded with carbon black can increase electrical conductivity by two orders of magnitude; the thermal drawing process naturally aligns these high-aspect-ratio nanofibers, resulting in highly conductive yet mechanically soft electrodes ideal for compliant in vivo neural probes [108]. Beyond simple conductors, composite engineering is also pivotal for mechanical sensing and acoustic applications [4, 41]. Embedding perovskite ceramic nanoparticles, such as barium titanate (BaTiO_3) or lead zirconate titanate (PZT), alongside CNTs into a poly(vinylidene fluoride)

TABLE 1 | Glass transition temperature T_g , Vicat softening temperature T_{vs} , thermal expansion coefficient α , and key remarks of common polymers found in thermally drawn fibers.

Materials	T_g ($^{\circ}\text{C}$)	T_{vs} ($^{\circ}\text{C}$)	α ($10^{-6} \text{ m}/(\text{m } ^{\circ}\text{C})$)	Remarks/common applications	Refs.
Polycarbonate (PC)	139–150	123–157	65–70	High strength and good optical clarity; widely used in optical waveguides, sensing fibers, and photonic elements	[41, 42, 80–82]
Poly(methyl methacrylate) (PMMA)	100–120	87–125	50–90	Transparent polymer with excellent optical properties; common in photonic preforms and microstructured fibers	[65, 83, 84]
Styrene–ethylene–butylene–styrene (SEBS)	– 90	~ 165	61–65	Elastomeric and highly flexible; used as soft cladding, stretchable interfaces, and deformation-sensing layers	[77, 79, 85, 86]
Low-density polyethylene (LDPE)	– 110	90–125	108–200	Flexible and electrically insulating; suitable as buffer layers or outer protective claddings	[87–89]
Polyvinylidene fluoride (PVDF)	– 42 to – 25	~ 136	128–140	High dielectric constant and piezoelectric capabilities; used in functional, capacitive, and porosity-engineered fibers	[4, 84, 88, 90]
Poly(lactic acid (PLA)/poly(d,l-lactic-co-glycolic acid) (PLGA)	60	150–170	60–80	Biodegradable thermoplastic with moderate stiffness; processable by thermal drawing within a narrow temperature window; used as structural, sacrificial, or biodegradable components in fibers	[87, 91]
Cyclic Olefin Copolymer (COC)	20–260	140–180	55–75	Amorphous, chemically resistant thermoplastic with a wide drawing temperature window; well-suited for cladding and structural support	[64, 92]
Polysulfone (PSU)	187–190	175–185	55–60	High-temperature engineering polymer; amber and semi-transparent; mechanically robust for structural fiber components	[93, 94]
Polyetherimide (PEI)	217–220	210–226	~ 100	Thermally stable with high mechanical strength; amber-transparent; compatible with glass-matched, high-temperature fiber architectures	[64, 95, 96]
Thermoplastic polyurethane (TPU)	– 49 to – 12	66–145	~ 57	Highly elastic and stretchable; ideal for wearable, deformable, and soft-electronic fiber systems	[97]
Polystyrene (PS)	63–112	~ 120	~ 70	Transparent but brittle with limited thermal stability; mainly used as a sacrificial support layer in preform-drawing processes	[87]

(PVDF) matrix significantly enhances the piezoelectric performance and acoustic transduction capabilities of the fibers without sacrificing flexibility [41, 109, 110]. Furthermore, advanced nanocomposites, such as metal-polymer blends formed via the controlled capillary breakup of metallic microwires into nanoparticles [111, 112], or catalytically active CNT-loaded polyethylene utilized for highly sensitive electrochemical biosensing (e.g., dopamine detection) [107], demonstrate the immense versatility of this approach. Ultimately, by judiciously formulating these composites, researchers can reconcile the thermo-mechanical and rheological mismatches between dissimilar materials during co-drawing, establishing a robust material foundation for high-performance, multifunctional smart textiles [49, 54].

2.4 | AI-Driven Innovation in Thermal Drawing Process

AI-driven process control for the thermal drawing process is emerging as a transformative research direction. The increasing availability of high-performance computational resources has enabled the development of control strategies based on ML, particularly deep reinforcement learning (DRL). DRL has demonstrated superhuman decision-making capabilities in complex environments [39, 115–117]. While ML has found growing use in manufacturing, for tasks such as cost estimation and quality prediction [118, 119], its application to real-time manufacturing process control remains limited. In this context, thermally drawn multimaterial fibers represent an exemplar system where data-driven control could offer significant advantages, as the process is governed by nonlinear thermo-viscoelastic behavior, multimaterial interactions, and stochastic fluctuations that challenge conventional controllers [102, 120]. A representative breakthrough is demonstrated by Kim et al. [39], who developed a DRL-based architecture capable of autonomously regulating fiber diameter during drawing. Their compact drawing platform (Figure 3a) provides real-time sensing of furnace temperature, feed speed, and draw tension while enabling closed-loop AI-based actuation. As shown in Figure 3b, the control framework uses a bootstrapped actor-critic reinforcement learning scheme built from four Long Short-Term Memory (LSTM) recurrent networks, an actor, a critic, and their corresponding time-delayed target networks. This design allows the controller to internalize the history of observations and actions, effectively resolving the partial observability imposed by the nonlinear and delayed thermal-viscoelastic dynamics of the thermal drawing process. Each network (Figure 3c) comprises five LSTM layers with 512 nodes per layer, recursively processing inputs over a temporal window to generate control actions. Unlike conventional Proportional-Integral-Derivative (PID) or model-predictive controllers, the DRL-based system requires no analytical or numerical models of the drawing process [121]. Instead, it learns optimal control policies directly by interacting with the physical machine, enabling predictive diameter regulation and accurate tracking of dynamically varying reference trajectories even under stochastic disturbances. This AI-based control paradigm offers several advantages for advanced fiber manufacturing. First, the recurrent architecture provides resilience to fluctuating process conditions, allowing rapid adaptation to new fiber geometries or draw profiles without parameter returning. Second, the ability to operate purely from real-time sensing data makes the method

compatible with complex multimaterial preforms whose thermo-mechanical behavior is difficult to model analytically. Third, simultaneous “train-control” threads enable continuous refinement of the controller during operation, pushing the system toward autonomous, self-optimizing manufacturing. However, these benefits come with trade-offs: the DRL controller requires substantial computational resources, long training periods, and careful management of exploration-exploitation strategies to avoid unstable draw conditions. Despite these challenges, the success of LSTM-based DRL frameworks demonstrates the strong potential of AI-enabled manufacturing to enhance reproducibility, minimize defects, and accelerate the scalable production of high-performance multimaterial fibers. Looking forward, the integration of AI-driven control with physics-informed rheological and fluid-dynamic models may accelerate the discovery of unconventional multimaterial combinations with disparate properties that can nevertheless be stably co-drawn into functional fiber architectures. Such approaches may further optimize interfacial compatibility, crystallization behavior, and capillary stability, enabling scalable fabrication of nanoscale metallic-glass, semiconducting, and hybrid multimaterial fibers for advanced sensing, energy, and bioelectronic applications [59, 100, 122].

3 | AI for Signal Processing in Thermally Drawn Fiber Sensing Systems

One of the most significant advancements in thermally drawn fibers is their use as sensing elements [52]. High-throughput fabrication enables the generation of large volumes of data; however, fiber-based sensing remains challenging due to inherent signal noise and limited output precision in some configurations [20]. These characteristics, data abundance, high throughput, and low accuracy, create an ideal environment for the application of AI and ML techniques. Consequently, the first large-scale intersection between AI and thermally drawn fibers has emerged in leveraging multifunctional fibers as sensors and applying conventional neural networks for signal classification. In this section, we review these developments and their implications for intelligent fiber systems.

3.1 | AI-Based Signal Processing for Stand-Alone Fiber Sensor Systems

A defining strength of multimaterial thermally drawn fibers is their ability to co-integrate multiple sensing modalities within a single, mechanically compliant strand, enabling truly stand-alone multifunctional sensing [50, 93]. Caglar and colleagues demonstrated such an architecture by embedding one capacitive electrode pair and two independent resistive electrodes within a single fiber cross-section (Figure 4a), allowing concurrent monitoring of resin flow propagation, curing kinetics, temperature, and mechanical strain in fiber-reinforced polymer composites [123]. However, because the resistance of carbon-black-filled polymer electrodes (e.g., cPE) is simultaneously modulated by thermal expansion and mechanical deformation, multisensory operation inherently introduces signal cross-sensitivity. To decouple these coupled effects, the authors implemented an artificial neural network trained using the Levenberg-Marquardt

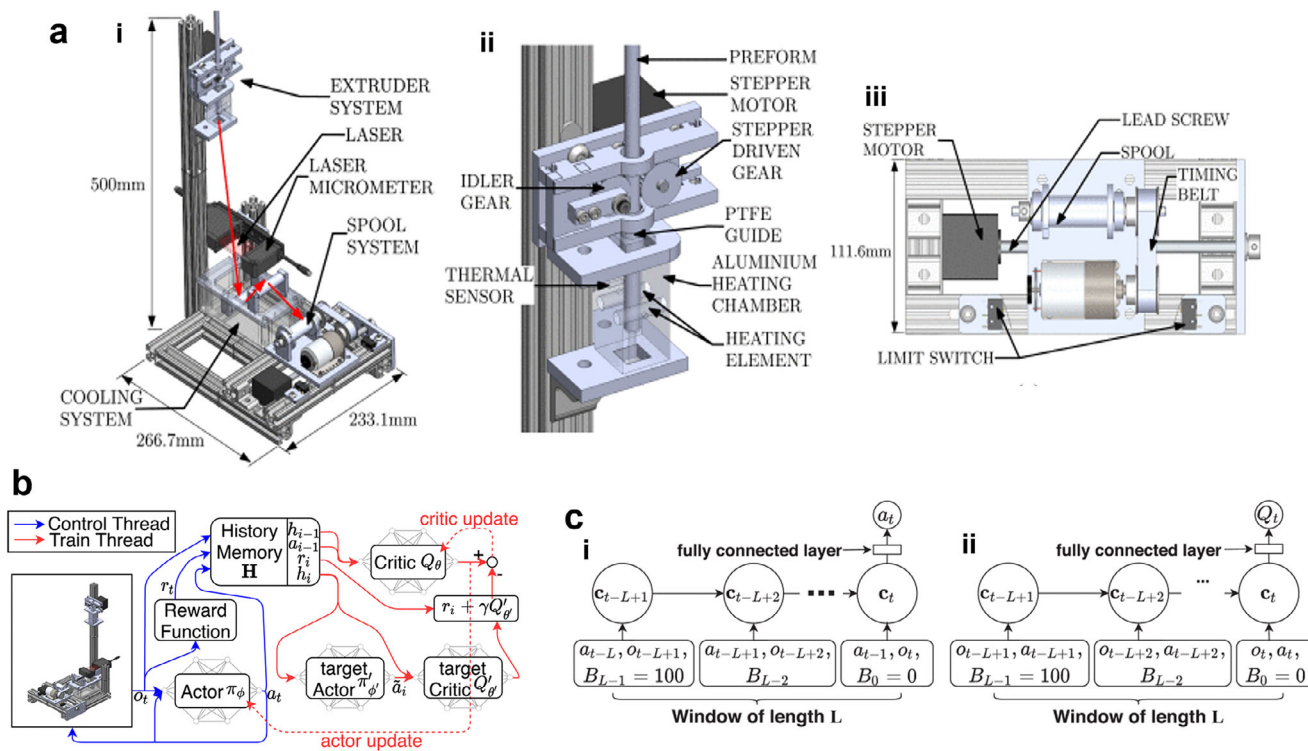


FIGURE 3 | Deep-reinforcement-learning-based control framework for fiber manufacturing. (a) Compact desktop fiber-drawing platform used for real-time DRL training and control: i) system overview; ii) extruder and heating assembly; iii) spool and take-up module. (b) Schematic of the learning architecture, illustrating the interaction between the control and training threads, the reward function, and the actor–critic networks with corresponding target networks. (c) Network architectures of the DRL model: i) actor network structure operating over a temporal window of length L ; ii) critic network structure processing state–action histories for value estimation. Reproduced with permission [39]. Copyright 2021, IEEE.

algorithm with three hidden layers (Figure 4b). Without requiring explicit constitutive models, the ANN accurately predicted temperature with deviations below $\pm 0.1^\circ\text{C}$ and reconstructed cyclic strain profiles with high fidelity across multiple thermal conditions (Figure 4c,d). This data-driven decoupling strategy not only circumvents the need for a priori physical parameterization but also demonstrates how AI-integrated multimaterial fibers can function as autonomous, scalable, and cost-effective sensing nodes for smart composite and ambient intelligence systems.

3.2 | AI-Driven Signal Processing and Classification for Healthcare-Oriented Smart Textiles Made With Thermally Drawn Fibers

AI is not limited to assisting the fiber fabrication process but increasingly operates across the entire fiber–fabric hierarchy, from real-time data interpretation and adaptive calibration to decentralized decision-making and system-level intelligence. When embedded within or coupled to thermally-drawn-fiber-based textile networks, AI enables fibers to evolve from isolated functional elements into cooperative, context-aware agents, supporting autonomous perception, learning, and response in intelligent textile systems [25].

For instance, recent advances in ML have substantially improved the analysis and classification of biomedical signals, such as electrophysiological signals (e.g., ECG, electromyography (EMG)),

photoplethysmography (PPG), and acoustic signals (e.g., phonocardiogram (PCG)), where ML has enabled accurate classification of cardiac conditions [124]. Yaseen et al. compared multiple classification algorithms, including K-Nearest Neighbors (KNNs), Deep Neural Networks (DNNs), and Support Vector Machines (SVMs), using mel-frequency cepstral coefficients (MFCCs) and discrete wavelet transforms (DWTs), achieving single-label accuracies as high as 97.9% ($F1 = 0.997$) in the classification of heart sounds signals [125]. However, their work remained restricted to single-label scenarios and did not validate feature relevance against known physiological signatures. Multi-label learning has also been explored for electrophysiological signals. Cai et al. introduced a residual neural network augmented with squeeze-and-excitation modules for ECG analysis, achieving a micro-F1 score of 0.863, though physiologically interpretable feature validation was not performed [126]. Building upon these developments, Carter et al. approach adopts mel-spectrogram-based 2D time–frequency representations to support multi-label classification (Figure 5a), enabling more direct comparison between ML-extracted features and physiological markers [127]. To enhance inference stability, Karim et al. employ an ensemble learning framework integrating Convolutional Neural Networks (CNN), SVM, and Random Forest (RF) classifiers, with soft-voting fusion to aggregate classifier confidence and improve predictive reliability (Figure 5b) [128].

Building on recent advances in ML, intelligent thermally drawn fiber-based biosensing platforms are emerging in which AI functions as a native system layer rather than a post-processing

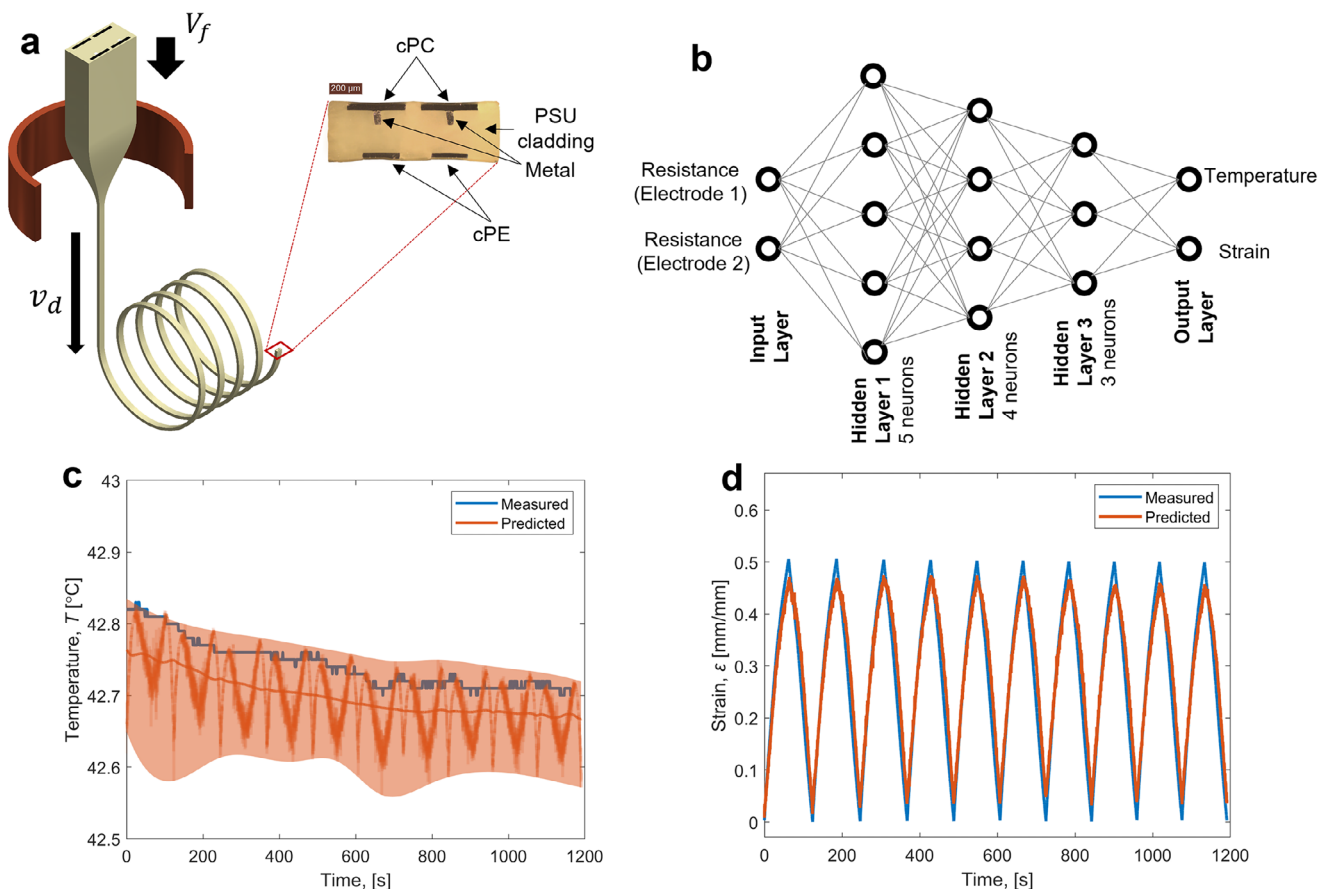


FIGURE 4 | ANN-enabled signal processing in multi-sensing polymer fibers. (a) Schematic of the thermal drawing process and representative micrograph of the fiber cross-section, showing embedded capacitive and resistive sensing elements. (b) Architecture of the ANN trained to jointly infer temperature and axial strain from multimodal electrical inputs. (c–d) comparison of measured vs. ANN-predicted (c) temperature and (d) strain throughout the test, demonstrating accurate separation of thermally and mechanically induced signals. Reproduced with permission [123]. Copyright 2021, Wiley-VCH.

module. Flexible fiber architectures integrating PPG, thermal, and strain-sensitive elements enable continuous, multimodal acquisition of physiological signals, including cardiac, respiratory, thermal, and biomechanical dynamics. These high-dimensional sensory streams are locally processed by AI-enabled microcontrollers and ultra-low-power wireless units, supporting in-fiber signal conditioning, feature extraction, and real-time inference [129]. The local deployment of ML models enables advanced physiological analytics, such as spectral analysis, heartbeat segmentation, arrhythmia detection, and activity recognition, thereby transforming textiles from passive sensing media into autonomous, closed-loop bio-interactive systems [20]. A seminal demonstration by Fink et al. exemplifies this technological trajectory: digital fibers incorporating sensing, memory, computation, and Bluetooth Low Energy (BLE) communication operate as distributed computational nodes within a garment (Figure 5c) [130]. Each fiber independently acquires PPG and triaxial accelerometry data, performs neural inference at 2-s intervals, and transmits probabilistic outputs to a coordinating fiber for federated decision aggregation. Whereas isolated fibers achieve <77% classification accuracy due to limited local data availability, the collective fabric network attains up to 95% accuracy in recognizing complex physical activities such as squats, lunges, planks, and arm motions, demonstrating how decentralized, in-

fiber ML markedly enhances robustness and inference fidelity through cooperative computation. Multimaterial fiber-based platforms incorporating conductive electrodes have likewise enabled high-fidelity ECG and EMG, facilitating continuous, noninvasive bioelectric monitoring with minimal motion-induced artifacts [18]. When combined with ML-based denoising, beat detection, and waveform classification algorithms [131, 132], these fiber systems can support on-body cardiovascular assessment, fatigue monitoring, and early screening of physiological stress.

Moreover, AI-enabled thermally drawn fiber-based textile systems are increasingly showing potential as key enablers of ambient intelligence for daily living environments, particularly for aging populations (Figure 5d). By 2050, the number of individuals aged ≥ 65 years is projected to increase from 700 million to 1.5 billion, intensifying the need for continuous and objective assessment of activities of daily living (ADLs) [133]. Impairment in ADLs is associated with a twofold increase in fall risk and up to a fivefold increase in one-year mortality [134, 135], while early detection and timely intervention can improve ADL performance by up to a factor of two [136]. Conventional ADL evaluations rely on infrequent self-reports or manual caregiver assessments, which are inherently subjective

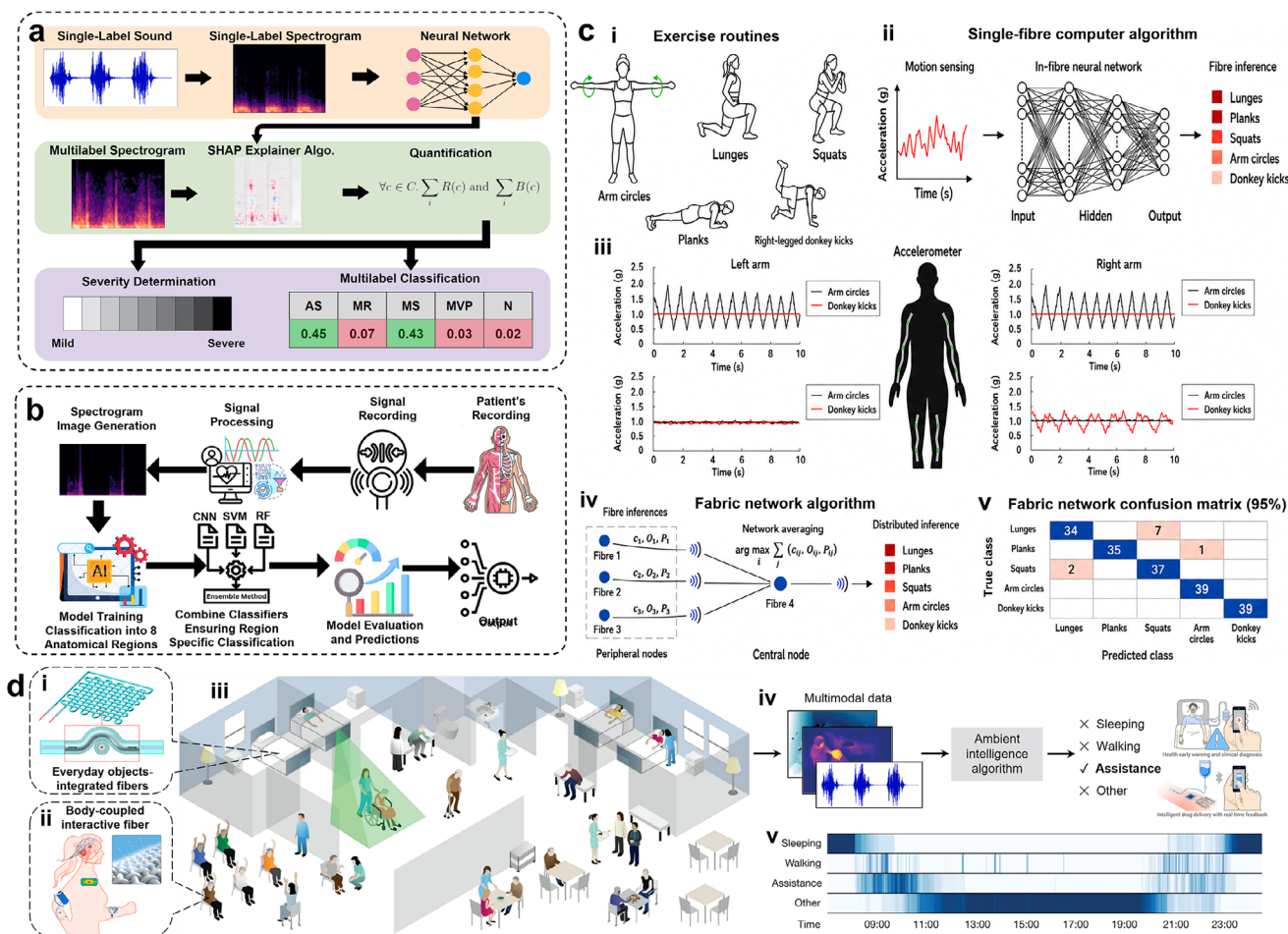


FIGURE 5 | Representative AI-driven frameworks for biomedical signal analysis, spanning end-to-end data processing pipelines and ensemble-learning-based anatomical classification systems. (a) Overview of the data-processing workflow, including signal acquisition, spectrogram generation, neural network training, result interpretation, and model evaluation. Reproduced with permission [127]. Copyright 2023, Elsevier. (b) Ensemble learning framework for classifying biomedical signals into eight anatomical regions. Percussion and palpation signals are transformed into spectrograms using Short-Time Fourier Transform (STFT) and normalization, then classified using an ensemble of CNN, SVM, and RF models to produce final predictions. Reproduced with permission [128]. Copyright 2025, Springer Nature. (c) Distributed activity classification using a network of fiber computers: i) five exercise routines used for training and testing; ii) each fiber independently acquires accelerometer data, performs onboard neural inference, and transmits outputs via Bluetooth; iii) representative acceleration traces; iv) schematic of fabric-level architecture in which peripheral fibers transmit precision-weighted results to a central coordinating fiber; and v) confusion matrix demonstrating enhanced accuracy through fabric-level aggregated inference. Reproduced with permission [130]. Copyright 2025, Springer Nature. (d) Ambient intelligence for daily living environments enabling continuous monitoring and timely assistance for patients: i) schematic of an integrated fiber architecture composed of two single-mode fibers (SMFs) and one multimode fiber (MMF) arranged in a grid structure and embedded into bedsheets, mats, or other everyday items; ii) body-coupled interactive fibers deployed as unobtrusive sensing interfaces; iii) implementation of the fiber-based system in an elderly home environment, operating in parallel with other ambient sensing modalities; iv) multimodal data collected from distributed sensors are processed by an ambient intelligence algorithm for activity recognition and categorization; v) daily activity summary of a patient over a single day, where darker blue regions indicate higher activity frequency. Reproduced with permission [133]. Copyright 2020, Springer Nature. Reproduced with permission [143]. Copyright 2021, IEEE. Reproduced with permission [144]. Copyright 2024, Elsevier. Reproduced with permission [145]. Copyright 2018, PMLR.

and insensitive to contextual factors such as caregiver assistance [137]. Ambient sensing approaches using depth, thermal, acoustic, radar, and radio-frequency modalities have demonstrated high performance, including assistance-detection accuracies of ~86% [138], ADL classification accuracies exceeding 90% [139], and fall-detection rates of 97%–100% with low false-alarm frequencies [140, 141]. However, their deployment remains limited by privacy concerns [142], environmental variability, and scalability challenges. Fiber-based ambient intelligence mitigates these limitations by embedding multimodal strain, pressure, thermal,

and optical sensors directly into everyday textiles and furnishings (Figure 5d(i)) [143, 144], enabling continuous, unobtrusive, and privacy-preserving monitoring. When coupled with distributed AI for real-time inference and decentralized decision-making, such systems support low-latency fall detection, caregiver alerting, and longitudinal behavioral profiling, positioning intelligent fiber networks as a critical technological bridge between passive observation and proactive clinical intervention in next-generation ambient healthcare ecosystems (Figure 5d(iv),(v)) [133].

3.3 | AI-Led Smart Sensing Fibers for Interactive Devices With Thermally Drawn Multimaterial Fibers

The integration of mechanosensitive fibers with advanced AI inference architectures provides a robust technological foundation for high-resolution human-machine interaction, distributed motion sensing, and structurally embedded protective systems. When incorporated into textiles or composite matrices, these thermally drawn fibers function as continuous, multi-degree-of-freedom sensing networks capable of spatiotemporally resolving strain, pressure, and thermal fields for real-time biomechanical and structural monitoring [146]. Recent advances in MEMS-integrated fiber devices [47, 74], together with fiber-embedded logic and memory enabling in-fiber computation [25, 147, 148], have substantially increased both the fidelity and dimensionality of acquired signals. These platforms transduce limb kinematics, joint articulation, and distributed surface-pressure profiles into structured electrical data streams with sufficient bandwidth and temporal resolution to support deep-learning and neuromorphic inference. Processing via CNNs, hybrid CNN-RNN models, or biologically inspired SNNs enables accurate recognition of complex gestures, tactile interactions, and dynamic motion trajectories [149].

Loke et al. demonstrated the feasibility of ML inference executed directly within thermally drawn fibers, in which neural-network parameters trained on body-temperature dynamics are compressed and permanently embedded in the digital memory of the fiber itself (Figure 6a) [47]. In this paradigm, sensing, feature encoding, and classification are co-localized within a single continuous filament, effectively eliminating the latency, energy overhead, and interconnect complexity associated with off-chip computation. This tight coupling of hardware and algorithmic functionality establishes a critical foundation for autonomous, fiber-native decision-making units that operate intrinsically within textile architectures rather than relying on external processing nodes.

This proof-of-concept further reveals the scalability of fiber-integrated intelligence toward gesture-based human-machine interaction interfaces (Figure 6b–d) [150–152]. Distributed strain, pressure, and deformation sensors embedded in smart gloves enable high-fidelity capture of fine motor activity and minimal inference latency. Multimodal fiber sensor arrays extend this capability to real-time, full-alphabet sign-language translation with sub-250 ms response times and near-perfect recognition accuracy (Figure 6c) [151], thereby providing an effective communication bridge between signers and non-signers. In parallel, scalable multimaterial fiber systems capture multidimensional hand kinematics to enable real-time control of virtual or robotic manipulators (Figure 6d) [152], underscoring the suitability of fiber-based sensorimotor interfaces for high-bandwidth decoding of human intent.

Beyond stationary interaction tasks, the integration of thermally drawn fiber sensing architectures into mobile and robotic control systems represents a technically promising yet still underexplored direction. Networks of mechanosensitive fibers embedded within gloves or garments continuously encode hand trajectory, velocity, and applied force (Figure 6e) [153].

When processed using lightweight temporal learning models, such as gated recurrent units, temporal convolutional networks, or compressed CNN-RNN hybrids, these multimodal signals can be transformed into stable latent representations for gesture-driven unmanned aerial vehicle (UAV) navigation. This interface paradigm bypasses conventional joystick-based control, offering a more intuitive, low-latency, and high-resolution modality for rapid aerial maneuvering and human-robot cooperative operations. AI-assisted generative modeling further expands the functional scope of thermally drawn fiber systems toward protective and structurally adaptive frameworks [154]. Reinforcement-learning-based optimization, topology optimization, and deep generative models enable the computational tailoring of fiber geometries, multimaterial stacking sequences, and mesoscale lattice architectures to maximize stiffness-to-weight ratios, enhance buckling resistance, or realize programmable deformation profiles. Such approaches facilitate the inverse design of lightweight, damage-tolerant, and morphing UAV frame structures capable of dynamically reconfiguring their aerodynamic or mechanical response based on data streams generated by the fiber network [155]. When these AI-optimized architectures are co-integrated with the intrinsic sensing capabilities of thermally drawn multimaterial fibers, the resulting structures function not only as load-bearing elements but also as interactive sensing interfaces. In this paradigm, mechanical deformation, contact forces, and environmental perturbations sensed by the embedded fiber network are continuously fed back into AI models that update control policies or structural states in real time, enabling closed-loop interaction between the device, the user, and the environment [156].

At the system level, thermally drawn fiber-based human-machine interfaces extend naturally into immersive and ambient intelligence environments (Figure 6f,g). Fiber-integrated socks and gloves incorporating triboelectric or strain-responsive elements enable real-time gait inference, full-body motion capture, and fine gesture recognition for Virtual Reality/Augmented Reality (VR/AR) interaction, rehabilitation, and fitness gaming [157]. At architectural scales, braided electronic cords and textile-embedded fiber sensors function as distributed tactile and environmental interfaces for smart-home control, security monitoring, and user-device communication [158]. These demonstrations illustrate how multimaterial fiber-enabled intelligence supports a continuous hierarchy, from in-fiber inference and personal human-machine interface to mobile robotic control and ambient protective infrastructures, establishing the thermal drawing process as a foundational platform for next-generation intelligent materials.

To transition from conventional systems tethered to bulky external instruments toward fully flexible and autonomous fiber networks, modern thermally drawn fibers can now seamlessly embed AI-enabled microcontrollers, digital memory, and ultra-low-power BLE communication modules directly within soft, mechanically compliant elastomeric claddings [47, 130]. This structural integration enables localized feature extraction and real-time edge inference natively within the fiber, effectively eliminating the mechanical constraints and latency associated with transmitting raw sensory data to external rigid hardware [20, 159]. Furthermore, to accommodate the strict energy budgets

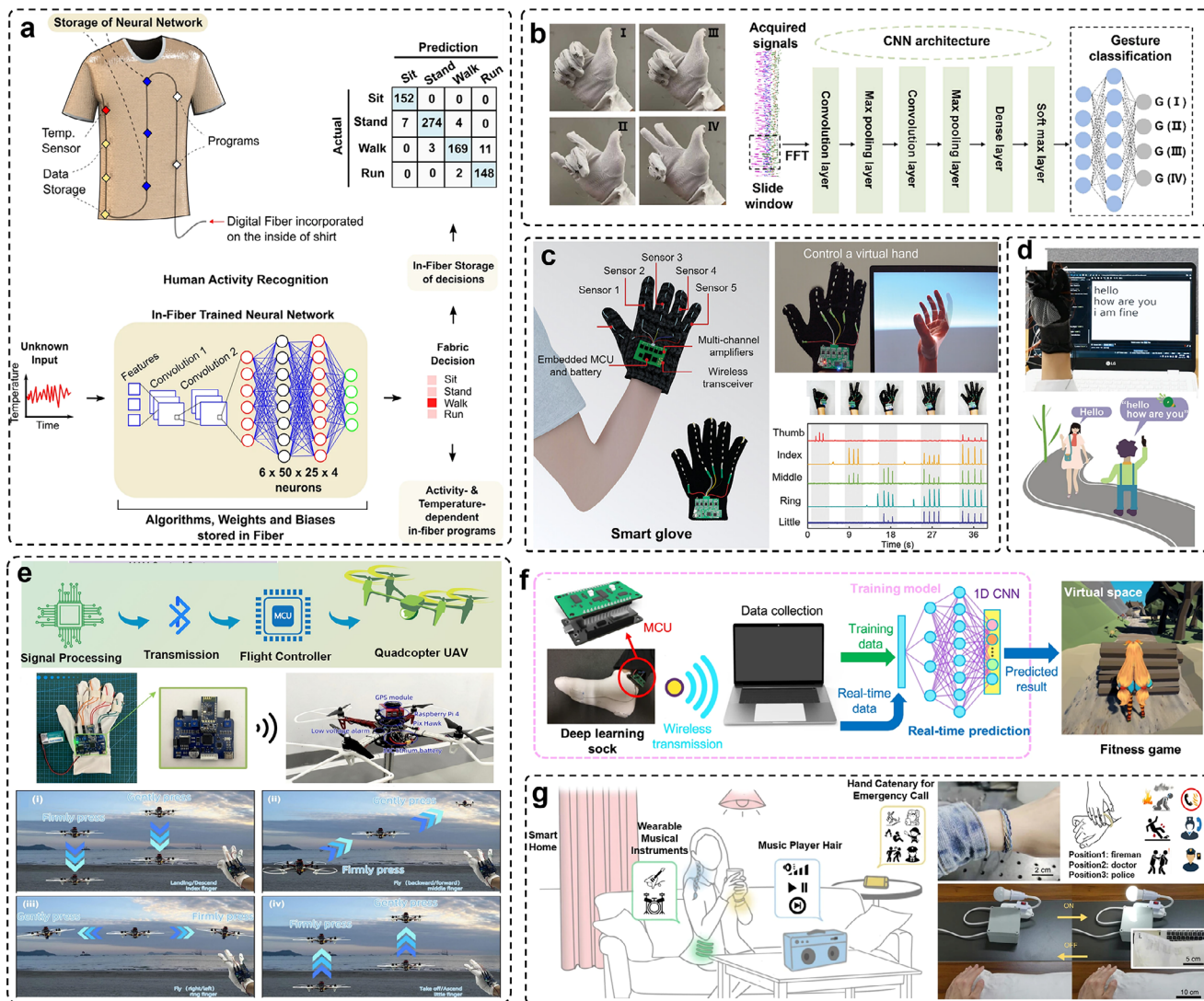


FIGURE 6 | Potential application of thermally drawn fibers for AI-enabled intelligent interactive systems. (a) In-fiber ML inference for human activity recognition: schematic of a garment integrated with digital fibers containing temperature sensors, data storage, and an embedded convolutional neural network capable of real-time activity classification. Reproduced with permission [47]. Copyright 2021, Springer Nature. (b) A smart glove integrating fiber-based sensors for hand-gesture recognition, with classification performed through deep-learning networks. Reproduced with permission [150]. Copyright 2022, Elsevier. (c) A sign-language translation glove that captures fine finger articulations, enabling real-time communication between a signer and a listener. Reproduced with permission [151]. Copyright 2021, Wiley-VCH. (d) A smart data-glove system for human-machine gesture collaboration, supporting both virtual-hand control and robotic-hand actuation. Reproduced with permission [152]. Copyright 2022, Springer Nature. (e) Concept of AI-assisted UAV control: a smart glove with piezoresistive fiber sensors interprets finger gestures to command drone movements, including takeoff, landing, and directional control. Reproduced with permission [153]. Copyright 2025, Elsevier. (f) Application of multimodal e-textiles in VR/AR control interfaces, demonstrated by smart socks designed for IoT-enabled gait analysis and immersive VR fitness interaction. Reproduced with permission [157]. Copyright 2020, Springer Nature. (g) Use of multimodal e-textiles in smart-home environments, exemplified by a braided electronic-cord interaction system for intuitive control of household devices. Reproduced with permission [158]. Copyright 2022, Springer Nature.

required for untethered, flexible operation, these self-contained systems are increasingly adopting neuromorphic computing and SNNs, which will be detailed in the Section 4 below [73, 160, 161]. By co-localizing multimodal sensing, memory, and event-driven computation directly within the flexible strand, this tight coupling of embedded hardware and decentralized AI shifts the design paradigm from externally supported smart fabrics to fully autonomous, untethered intelligent textile networks [47, 49, 162].

4 | Emerging AI Approaches for Smart Textile Systems Based on Thermally Drawn Fibers

Beyond signal processing, achieving intelligent functionality requires to simultaneously optimize multiple technical domains within the fiber-fabric system, including computational capability, sensing and measurement fidelity, communication efficiency, and energy management, as illustrated in Figure 7a [25]. These four functional property types collectively define how embedded

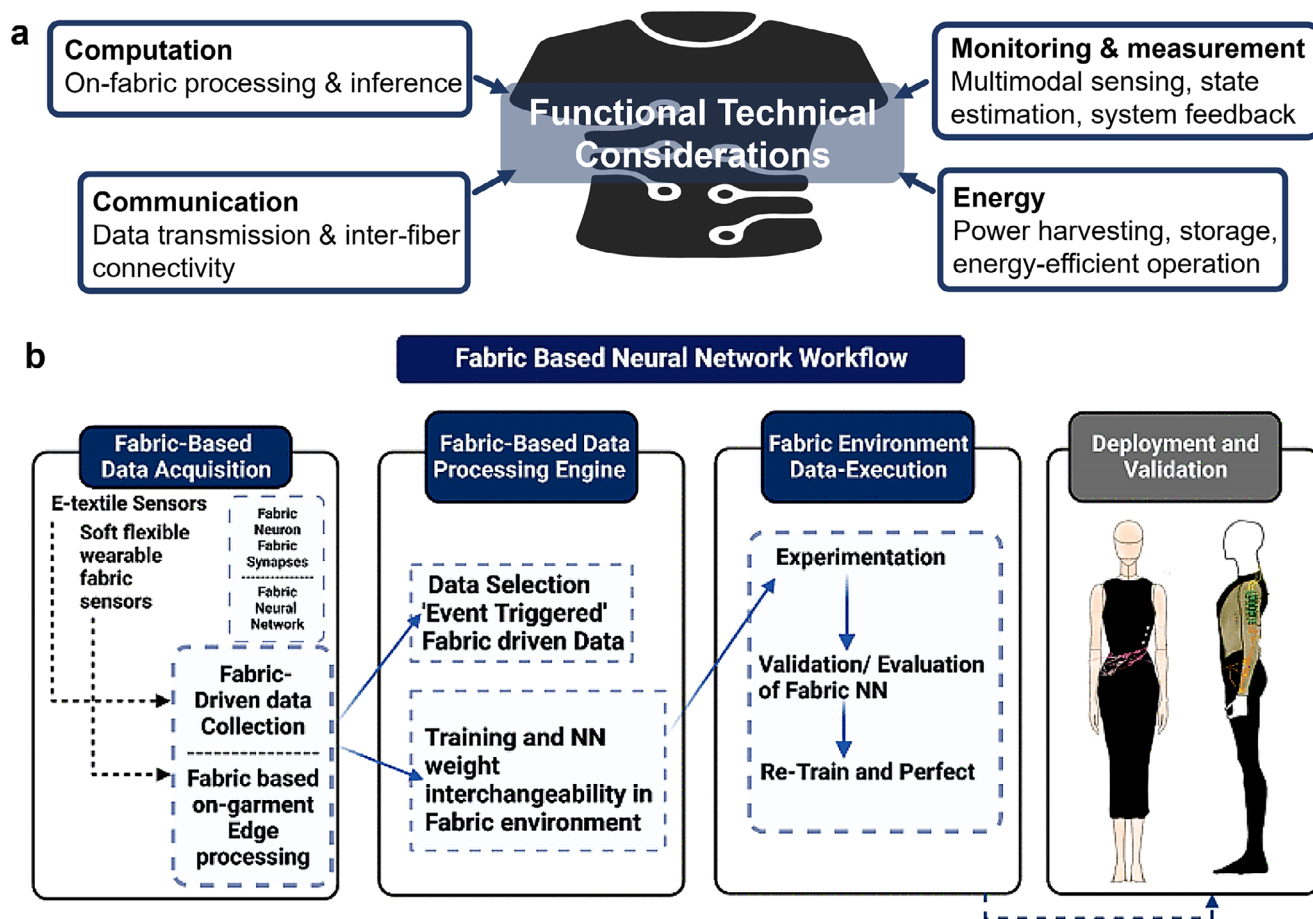


FIGURE 7 | Framework for the development and implementation of fabric-embedded AI. (a) Key technical factors to consider for embedded fabric-based textile intelligence. (b) Fabric-driven neural network process. Reproduced with permission [25]. Copyright 2023, IEEE.

AI can sense, process, and respond efficiently within thermally drawn fiber architectures, ensuring that performance, adaptability, and sustainability coexist in the next-generation of smart textiles. Recent developments further illustrate how AI-driven data architectures can be physically implemented within fiber and fabric systems [36]. For instance, magnetically encoded conductive fibers have been demonstrated to store binary information (0 or 1) using ferromagnetic polarity, enabling wearable authentication or data encryption at the textile level [163]. Similarly, optical and piezoelectric fibers can detect human physiological signals, such as heart rate, muscle activity, and motion, through embedded sensors and communicate the processed information via optical or electrical pathways to external devices [20, 47, 52, 123, 130]. The resulting systems combine on-body data collection, transmission, and processing into a single textile layer, transforming garments into active computational fabrics.

In parallel, developing AI systems capable of operating directly within fabric environments poses challenges fundamentally distinct from those of conventional digital computation [164]. A long-standing bottleneck has been the reliability of electrical and mechanical interfacing between functional fibers, textile architectures, and external electronics, particularly under repeated deformation, laundering, and prolonged use [20]. Recent progress in compliant electrodes [22, 89, 165], soft interconnects [77], fiber-textile integration strategies [46], and encapsulation technolo-

gies [87] has significantly alleviated these constraints, enabling improved signal integrity and mechanical robustness during textile processing and cyclic loading. Within this context, fiber-based AI architectures must simultaneously reconcile mechanical compliance, distributed signal transmission, and ultra-low power operation with long-term durability [159]. Emerging paradigms therefore propose fabric neural networks, in which individual fibers function as analogs of neurons and synapses, forming localized computational clusters within the woven matrix. Information is processed hierarchically, spanning fiber-level sensing and learning to fabric-level inference, thereby emulating key organizational principles of biological neural systems [166, 167].

While conventional e-textiles that typically function as passive data conduits requiring bulky external processors, the thermal drawing process uniquely addresses these demands by enabling the monolithic co-integration of conductors, semiconductors, and functional dielectrics within a single, continuous strand [19, 22, 54]. This intrinsic architectural capability transforms the thermally drawn fiber into an active, self-contained computational node that co-localizes sensing, memory, and processing, offering a fundamental hardware advantage for low-latency, decentralized in-fiber intelligence [47, 130]. As schematically illustrated in Figure 7b, thermally drawn fibers would be particularly suited for fabric-centric AI workflows that integrate embedded fiber sensing, local in-fiber processing, textile-level actuation, and

feedback-driven learning supported by edge or cloud intelligence [25]. These elements establish a closed-loop coupling between digital computation and material response, underpinning the development of autonomous, adaptive, and scalable smart textile systems.

4.1 | Spiking Neural Network Properties Inspiring Next-Generation Multimaterial Fiber Intelligence

SNNs represent an advanced subclass of ANNs that more faithfully recapitulate the biophysical and electrophysiological dynamics of the human nervous system through electronic analogues of neurons and synapses [168]. Learning in SNNs emerges from the iterative, activity-dependent modulation of synaptic weights, enabling temporally resolved, event-driven computation. Foundational neuron models, including the Leaky Integrate-and-Fire (LIF) model [169–171], the Spike Response Model (SRM), and the Hodgkin–Huxley model [170], provide the mechanistic and mathematical framework required for their electronic realization. Building upon these principles, a new generation of artificial synaptic fiber architectures capable of processing multi-input, spike-encoded signals has recently gained traction as a promising platform for neuromorphic sensing, computation, and actuation (Figure 8a–e) [172]. Early experimental realizations include the fiber-shaped synaptic device based on ferroelectric organic transistors reported by Ham et al., which demonstrated key synaptic behaviors such as potentiation and depression in a textile-compatible form factor [173]. Subsequently, Wang et al. developed a reconfigurable two-terminal textile memristor exhibiting both nonvolatile synaptic plasticity and volatile neuron-like dynamics, enabling thermally adaptive learning behaviors within fabrics (Figure 8b) [73]. Extending neuromorphic functionality beyond electronics, Chen et al. introduced a fiber-shaped optoelectronic synapse capable of optical sensing, in-fiber memory storage, and digital information imaging, highlighting the potential for multimodal perception and processing in woven systems (Figure 8c) [167]. These integrated synaptic fibers recapitulate essential neurobiological operations, stimulus integration, spike initiation, signal propagation, and neuromuscular-like actuation, thereby supporting multisensory encoding and closed-loop feedback control across distributed material networks [166, 174].

Building directly upon the emergence of SNN and fiber-shaped synaptic devices discussed above, recent advances in neuromorphic circuit design indicate that incorporating multi-input pathways analogous to dendritic integration, synaptic junctions, and axonal signal propagation enables highly energy-efficient, event-driven information processing [175]. Inspired by the fascicular organization of neuronal bundles, arrays of artificial synaptic fibers can be woven into textiles to form spatially isolated and distributed neuromorphic networks. These networks support parallel signal transmission and local computation, enabling functionalities that are difficult to achieve with conventional CMOS architectures limited by planar geometry, high power consumption, and von Neumann bottlenecks [166]. Extending beyond sensing and computation, such fiber-centric neuromorphic architectures intrinsically reduce system-level circuit complexity by co-localizing perception, processing, and actuation within the same material framework, thereby enabling direct ana-

log control of artificial yarn muscles and coordinated mechanical responses, including bending, translation, and load lifting. However, realizing this vision requires artificial synaptic fibers that combine high mechanical compliance, multidirectional sensing, and full compatibility with textile manufacturing processes. To date, most reported implementations remain limited to a narrow set of fiber chemistries fabricated primarily via dip-coating and related post-processing methods, with scarce demonstrations of scalable system-level integration. In contrast, the thermal drawing process, by virtue of its ability to co-draw conductors, semiconductors, electrolytes, and functional oxides into a single, continuous fiber, offers a powerful and largely untapped pathway toward scalable, energy-efficient neuromorphic fiber systems with substantially enhanced architectural complexity and functional diversity.

4.2 | Computational Architecture and Artificial Fiber Neurons

The conceptual framework of SNNs provides a bioinspired model for distributed computation within fiber systems. Each fiber can integrate multiple functional domains, metallic contacts, semi-conducting cores, and ionic conductors, that collectively operate as interconnected neural nodes. Analogous to biological neurons, charge accumulation within these regions defines a fiber's "membrane potential," and once a threshold is surpassed, a transient current spike is generated and propagated through the conductive pathway, emulating neural firing and synaptic transmission [176, 177]. The simplest fiber-based neuron follows the LIF principle [45], in which resistive (R) and capacitive (C) elements, such as conductive polymer electrodes and dielectric polymer claddings, govern integration and leakage dynamics (Figure 9a) [178]. "Integration" corresponds to charge or mechanical energy accumulation, whereas "leakage" arises from dielectric relaxation or viscoelastic dissipation in the polymer matrix. Upon reaching critical potential, a discharge event occurs, producing a spike that transmits information. This event-driven mechanism can be realized using conductive polymers (PEDOT:PSS, polyaniline), ferroelectric copolymers [P(VDF-TrFE)], or graphene-polymer composites co-drawn within flexible insulators.

For more complex and biologically realistic dynamics, the Hodgkin–Huxley model can be conceptually adapted to fiber systems (Figure 9b) [179], representing ion transport through K^+ and Na^+ channels as voltage-dependent resistive and capacitive components. Temporal coding further extends this analogy by encoding information in the precise timing of spikes, using latency, delta-modulation, or inter-spike interval schemes [180–182]. Compared with rate coding, temporal coding provides higher processing efficiency and data sparsity, aligning naturally with event-driven computation but requiring high temporal precision. Figure 9c illustrates rate and temporal encoding schemes, where stimulus intensity is represented either by a spike rate or by spike timing, and classification is determined by the neuron with the highest firing rate or the earliest spike, respectively [180]. The end-to-end processing of sensory information using SNNs is depicted in Figure 9d, where raw sensor outputs are pre-processed and encoded into spike trains that propagate through the network to generate predictions such as image reconstruction, inference results, or contextual information. During training, predicted

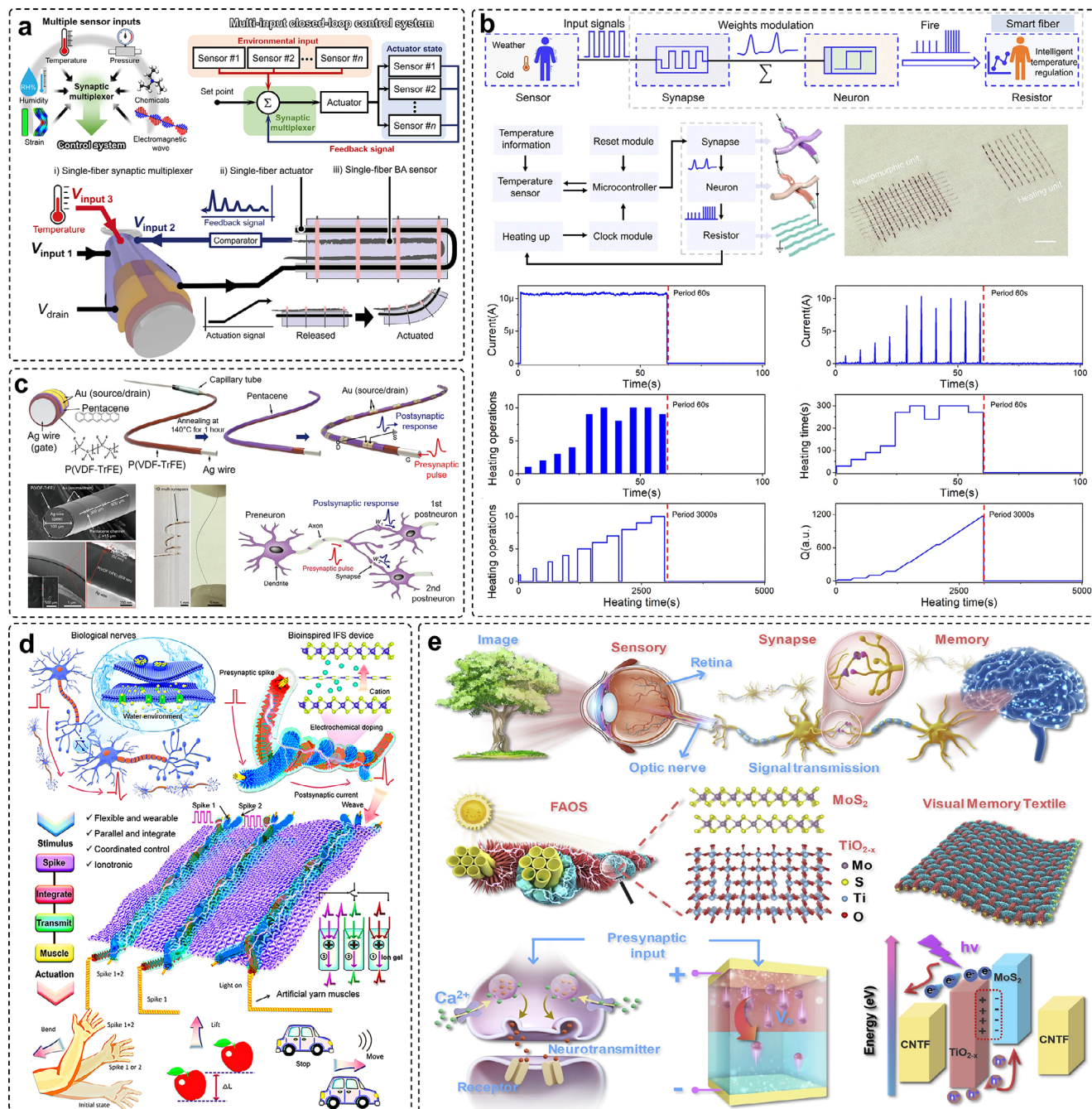


FIGURE 8 | Architectures and device-level realizations of artificial synaptic fibers enabling neuromorphic sensing, computation, and actuation. (a) System-level architecture and signal flow of an artificial synaptic multiplexing unit designed for multi-input neuromorphic control. The schematic illustrates the convergence and integration of heterogeneous sensory inputs within a synaptic fiber network, resulting in spike-encoded outputs that drive a closed-loop control system comprising an artificial actuator and feedback elements, such as a bending-angle (BA) sensor, thereby emulating sensorimotor loops observed in biological nervous systems. Reproduced with permission [174]. Copyright 2022, AAAS. (b) Fiber-based neuromorphic thermal regulation system integrating an artificial synapse, an artificial neuron, and a resistive heating element within a single textile-compatible platform. Synaptic current responses are transduced into neuron-like spiking signals that modulate the Joule heating behavior of the embedded resistor, enabling closed-loop, adaptive thermal control. Photographs of the fabricated fiber memristor heater and representative current–time and temperature–time profiles highlight the device architecture and neuromorphic heating dynamics. Reproduced with permission [73]. Copyright 2022, Springer Nature. (c) Fabrication workflow and structural characterization of a one-dimensional organic artificial multi-synapse fiber. The process schematic details the sequential construction steps, while cross-sectional and top-view scanning electron microscopy images reveal the internal architecture and surface morphology of the device. Optical images demonstrate the fiber’s mechanical flexibility, including stable coiling around a 1.2-mm-diameter glass tube. An accompanying schematic of a biological multipolar neuron underscores the functional analogy between synaptic weight modulation in the artificial fiber and postsynaptic signal integration in neural systems. Reproduced with permission [173]. Copyright 2020, AAAS. (d) Bioinspired wearable neuromorphic sensorimotor textile incorporating quasi-solid-state iontronic synaptic fibers. The schematic depicts a distributed architecture in which ion-based signal transmission, local neuromorphic processing, and coordinated actuator control are integrated within a woven platform, illustrating how

outputs are compared with ground-truth targets, and parameters are updated through supervised (e.g., surrogate gradient learning) or unsupervised (e.g., Spike-Timing-Dependent Plasticity, STDP) learning, or via ANN-to-SNN conversion [168]. Realizing fabric-based neural circuit models requires the co-integration of R and C elements with tunable electrical characteristics, interconnected using conductive thread [183, 184]. While prior approaches have relied on discrete textile components, such as fabric potentiometers, zipper-based variable resistors, or stretchable conductive fabrics, to emulate variable resistance [185], these implementations remain mechanically complex, difficult to scale, and poorly suited for distributed neuromorphic operation. In contrast, thermally drawn multimaterial fibers provide a unified materials platform in which R, C, and conductive elements can be monolithically co-drawn within a single, continuous fiber architecture, enabling spatially programmable electrical responses without moving parts [186]. This intrinsic co-integration integrates sensing, signal conditioning, and circuit functionality into a fiber-level building block, which is fully compatible with textile manufacturing. When combined with SNN paradigms, such fiber-based circuits naturally support event-driven, asynchronous signal processing directly at the material level, enabling an end-to-end neuromorphic pipeline, from sensing to inference, without the frame-based discretization required by conventional CNN-based approaches [180].

4.3 | Artificial Synapses and Learning in Fiber Networks

Learning in biological neural systems is fundamentally governed by synaptic plasticity, whereby synaptic weights are dynamically modulated in response to neural activity and environmental stimuli [187]. Translating this principle into intelligent fiber-based systems requires the development of artificial synapses with electrically tunable conductance, hysteretic behavior, and nonvolatile state retention, enabling fibers to encode, store, and update information in a learning-dependent manner [188]. Within thermally drawn and coated fiber architectures, such synaptic functionalities can be implemented using embedded memristive junctions, ferroelectric layers, or ion-gel-gated transistor structures, which permit localized modulation of charge transport and long-term memory retention directly at the fiber level. Recent demonstrations employing graphene oxide and reduced graphene oxide coatings on conductive yarns have shown mechanically robust, deformation-tolerant resistance modulation, establishing a viable materials basis for adaptive synaptic interconnects in textiles [189]. Likewise, ferroelectric organic transistors integrated onto metallic microwires have been shown to emulate both excitatory and inhibitory synaptic responses, providing analog memory and learning capability while main-

taining the mechanical compliance required for fiber and textile integration [173].

When assembled into larger architectures, networks of such learning-enabled fibers naturally parallel the organizational principles of ANNs, in which information processing emerges from distributed connectivity and weighted signal propagation. Table 2 compares feedforward and recurrent network architectures with respect to their suitability for SNN implementations in fiber-based neuromorphic systems. The feedforward architectures are well-suited for static pattern recognition tasks [190, 191], whereas recurrent and spiking models more effectively capture temporal correlations, event-driven dynamics, and continuous-time signal evolution. These characteristics make fiber-based synaptic networks particularly well aligned with temporal and spatiotemporal learning paradigms, positioning artificial synaptic fibers as foundational building blocks for distributed, adaptive, and learning-capable material systems.

4.4 | Spatiotemporal Processing and Communication Through Spikes

Spiking networks intrinsically encode and process information in the temporal domain, operating on discrete, time-resolved events rather than static data representations. This mode of computation is particularly well-suited to thermally drawn multimaterial fiber systems, as they are continuously exposed to dynamic and multimodal stimuli, including mechanical vibration, pressure, humidity, and temperature fluctuations [192]. In such systems, individual sensory perturbations can be transduced into spike trains that propagate through conductive or optoelectronic pathways embedded within the fiber network with high temporal fidelity. Advanced fiber architectures may incorporate optical waveguides, piezoelectric layers, ion-conductive channels, or microelectronic interposers to support spike-based communication and routing. By enabling localized processing at the fiber node level, spiking fiber networks can perform early-stage detection and classification of transient events, transmitting only sparse, task-relevant features, such as spike timing, rate, or temporal patterns, to neighboring fibers. This asynchronous, event-driven communication paradigm substantially reduces energy consumption relative to continuous analog or frame-based data transmission. Recent proof-of-concept demonstrations, including wearable neuromorphic systems integrating textile pressure sensors with spiking circuits, have already achieved real-time tactile stimulus classification using spike-based encoding and processing [45]. Extending these principles to thermally drawn multimaterial fiber platforms opens a pathway toward textile- and composite-scale networks capable of autonomously recognizing spatiotemporal patterns associated with deformation,

neural organizational principles can be translated into interactive, body-mounted systems. Reproduced with permission [166]. Copyright 2024, NAS. (e) Conceptual design of a fiber-addressable optoelectronic synapse (FAOS) and its prospective integration into textile-based visual perception and memory systems. Inspired by human visual and mnemonic pathways, the architecture employs a $\text{MoS}_2/\text{TiO}_2-x$ heterojunction synaptic structure to enable optoelectronic signal processing and in-fiber information storage, highlighting opportunities for multimodal neuromorphic textiles with embedded visual memory functionality. Reproduced with permission [167]. Copyright 2023, Cell Press.

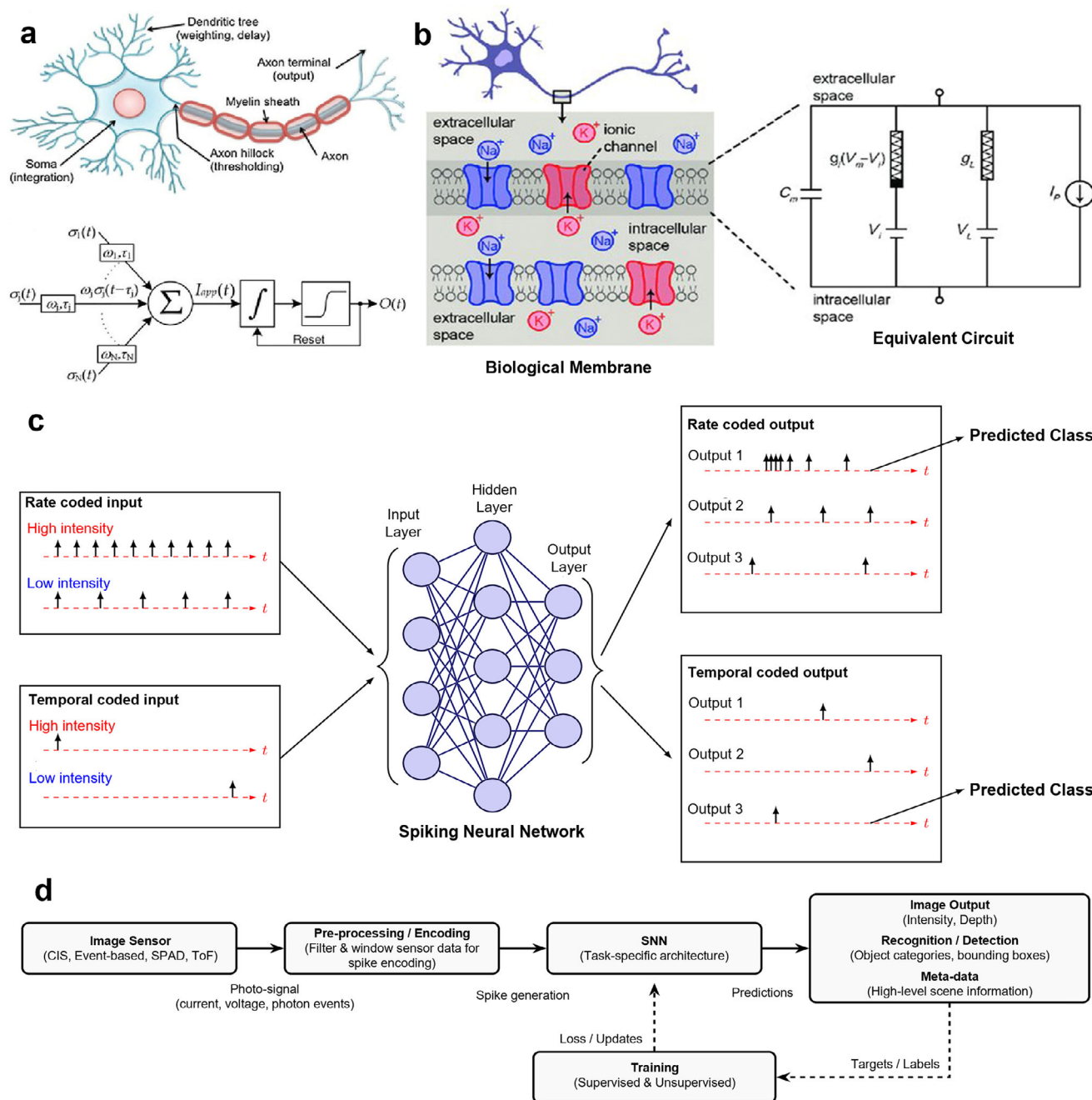


FIGURE 9 | Fundamental neuronal models and computational principles underpinning SNNs. (a) Schematic and operation of a LIF neuron. Weighted and time-delayed synaptic inputs are integrated at the soma with passive leakage. When the membrane potential crosses the threshold, the neuron generates a spike that is transmitted to downstream neurons. Reproduced with permission [178]. Copyright 2014, Springer Nature. (b) Hodgkin-Huxley model of a biological neuron. The model describes the initiation and temporal evolution of action potentials based on ion transport across the neuronal membrane. The membrane separates intracellular and extracellular electrolytes containing Na^+ , K^+ , and Cl^- ions, forming an effective capacitor due to concentration gradients. Ion-specific channels and gating mechanisms operate in parallel on the membrane surface, producing ionic currents that, together with leak and passive pathways, constitute the equivalent membrane circuit shown on the right. Reproduced with permission [179]. Copyright 2020, Springer Nature. (c) Input spike encoding under rate and temporal coding schemes, where high-intensity stimuli are represented by higher firing rates or earlier spike times. Classification is determined by the neuron with the highest firing rate or the earliest spike. (d) Flowchart of SNN-based image processing, illustrating sensor data acquisition, spike encoding, network inference, and parameter updates during training. Reproduced with permission [180]. Copyright 2025, MDPI.

TABLE 2 | Neural network types relevant to SNNs.

SNN Type	Data flow	Memory	Prediction	Weights
<i>FeedForward</i>	Unidirectional propagation from input to output layers	No intrinsic memory; does not retain past states	Limited; suitable for static or instantaneous inference	Fixed weight matrix applied only to the current input to generate output spikes
<i>Recurrent</i>	Cyclic or feedback connections enabling looping information flow	Possesses temporal memory; capable of encoding and learning time-dependent patterns	Strong; effective for sequential, temporal, or context-dependent tasks	Weights influence both current inputs and internal states from previous time steps

acoustic excitation, or physiological signals, thereby enabling truly distributed intelligence embedded within material systems [123].

5 | Current Challenges and Perspectives on AI-Integration in Thermally Drawn Multimaterial Fibers

Through the thermal drawing process, multimaterial fibers are transformed from passive structural or electronic components into computationally active material systems operating at the intersection of materials science, embedded electronics, and machine intelligence. Despite substantial recent progress, several critical challenges must be addressed to fully realize the potential of AI-enabled intelligent multimaterial fibers:

i) Materials compatibility and thermal stability during drawing: The high-temperature, high-viscosity environment of the thermal drawing process constrains selectable materials due to mismatches in viscosity, thermal expansion, and chemical stability. Interdiffusion, delamination, void formation, and structural instabilities remain persistent limitations. Low-temperature precursor-based drawing, interface engineering, and composite preforms represent promising strategies to expand the material palette to include high-performance semiconductors, ferroelectric materials, ionotronic conductors, and memristive nanomaterials.

ii) Electrical and mechanical durability of output contacts: a major and under-investigated challenge for thermally drawn multimaterial fibers lies in establishing reliable electrical contacts. Due to the microscale dimensions of embedded electrodes, these fibers exhibit very high resistance, and the contact formation remains an underexplored bottleneck for their deployment as stand-alone devices. Currently, there is no scalable, automated method for extracting signals from fibers. Conventional approaches, such as silver paste application or soldering, are often unreliable, particularly in wearable systems where fibers must maintain electrical, mechanical, and functional stability under repeated deformation, perspiration, washing, and eventually exposure to biological fluids [80, 193]. Addressing this issue will require innovations in multi-encapsulation, moisture-resistant interface treatment, and advanced approaches such as self-healing materials or functional coating.

iii) Energy autonomy and power management: Distributed fiber networks necessitate integrated energy harvesting and storage solutions. Developments in piezoelectric [194], triboelectric [7, 195], thermoelectric [196, 197], and photovoltaic fibers [198], coupled with AI-optimized power routing and load balancing, will be key to enabling fully autonomous fiber systems with minimal external power requirements.

iv) Data security, uncertainty, and ethical considerations: As intelligent fibers begin to collect sensitive physiological, behavioral, and environmental data, issues of data privacy, encryption, authentication, and ethical data governance will become increasingly critical. Edge inference and federated learning architectures, where data remain local to the fiber or fabric node, present promising pathways to mitigate security and privacy concerns.

v) Computational efficiency and neuromorphic adaptation: AI models deployed within fibers must be lightweight, energy-efficient, and capable of real-time adaptation. Neuromorphic and SNN-based paradigms offer biologically inspired solutions that align with the intrinsic constraints of fiber-scale devices. The emerging concept of a “Moore’s law for fibers,” in which integrated functionalities, logic, memory, sensing, energy storage, scale exponentially within continuous fiber architectures, is increasingly reflected in demonstrations of digital fibers capable of onboard inference, memory retention, and data logging.

The following subsections present an in-depth analysis of these critical challenges, addressing their implications across materials science, device engineering, and system-level integration. By examining both current bottlenecks and emerging solutions, we aim to outline several strategies for developing robust, scalable, and intelligent fiber architectures. These architectures are envisioned to seamlessly integrate sensing, computation, and communication, enabling next-generation textile systems with enhanced functionality and adaptability.

5.1 | Material and Structural Design Considerations

Implementing SNN-inspired architectures within thermally drawn fibers requires stringent control over material compatibility and hierarchical structural design. Achieving stable co-drawing demands that all constituent materials, polymers, metals, semiconductors, and functional oxides, possess closely

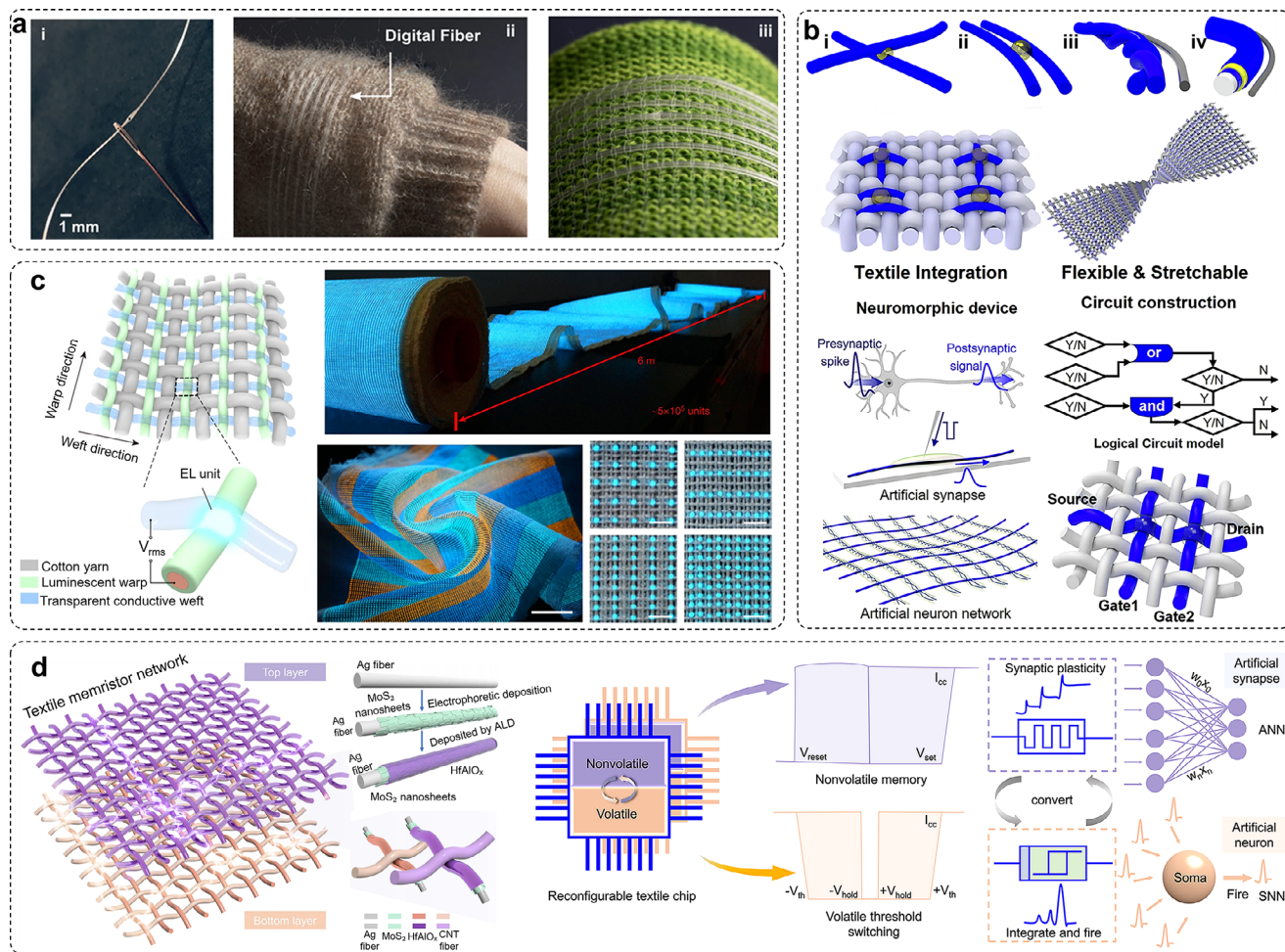


FIGURE 10 | Integration and textile-level implementation of functional fibers. (a) Demonstration of fiber integration into conventional textile structures. The images illustrate representative steps in incorporating functional fibers into garments and fabrics, including i) threading through standard sewing tools, ii) embedding within knitted apparel, and iii) incorporation into woven textile architectures. Reproduced with permission [47]. Copyright 2021, Springer Nature. (b) Representative geometries of fiber-based organic electrochemical transistors (F-OECTs) illustrating the versatility of multi-fiber architectures. Configurations include i) cross-aligned, ii) parallel, iii) twisted, and iv) coaxial structures, each offering distinct mechanical and interfacial properties for textile integration. The bottom schematic highlights conductive and semiconducting fiber elements along with their characteristic attributes, flexibility, stretchability, and enhanced surface area, supporting seamless incorporation into wearable fabrics and enabling circuit-level functionalities such as neuromorphic operation. Reproduced with permission [201]. Copyright 2025, Springer Nature. (c) Schematic representation of a generalized woven textile architecture incorporating functional fiber elements. Each fiber–fiber intersection forms an operational unit whose response is determined by the materials and structural configuration at the crossing point. Large-area textile prototypes demonstrate scalability over meter-long lengths and the ability to maintain functionality under complex deformation modes such as bending, twisting, and draping. Variations in weave parameters enable tunable spatial distribution and density of active units across the fabric (scale bars as indicated). Reproduced with permission [162]. Copyright 2021, Springer Nature. (d) Schematic illustration of a textile-integrated memristor network comprising a top-layer device exhibiting synaptic plasticity and a bottom-layer device implementing neural threshold-switching behaviors. The fiber-based memristor incorporates an Ag/MoS₂/HfAlO_x/CNT heterostructure, as shown in the device micrograph (scale bar: 40 μm). The reconfigurable textile chip demonstrates both nonvolatile memory states and volatile integrate-and-fire responses, enabling neuromorphic functionality directly within woven architectures. Reproduced with permission [73]. Copyright 2022, Springer Nature.

matched softening temperatures, rheological behaviors, and thermal expansion coefficients to maintain interfacial cohesion and prevent delamination, void formation, or geometric distortion during draw-down. Within this framework, dielectric matrices such as PC and cyclic olefin copolymers offer mechanical robustness and low-loss insulation, while ferroelectric polymers such as P(VDF-TrFE) provide remanent polarization states essential for long-term synaptic weight retention and STDP-like plasticity [25, 199]. Building on these material foundations, recent advances in thermal drawing have expanded the structural design space of

neuromorphic fibers. As shown in Figure 10a, thermally drawn fibers can now be seamlessly integrated into woven, knitted, and embroidered textile architectures without compromising flexibility or scalability [200], thereby creating a mechanically compliant platform in which artificial synapses, neurons, and interconnects can be spatially organized [47]. This ability to embed functional fiber elements directly into textile substrates establishes the structural basis upon which higher-order neuromorphic architectures can be constructed. Structurally, fibers made with the thermal drawing process can be engineered

into multicore, coaxial, or multilayered configurations that mirror the hierarchical organization of biological neural circuits. As illustrated by the prospective geometries and logic-building motifs in Figure 10b–d, crossed, parallel, twisted, coaxial, and memristive fiber networks represent promising architectures for future neuromorphic fiber-based systems [73, 162, 201]. These configurations provide inherent mechanical compliance and compatibility with textile processes while enabling functional operations such as synaptic plasticity, spike generation, logical gating, and integrate-and-fire computation within deformable fabric substrates. The intrinsic scalability of the thermal-drawing process allows these neural architectures to be produced as kilometer-long continuous fibers with uniform cross-sectional fidelity, achieving reproducible connectivity and device density far beyond conventional lithographic methods.

To emulate multilayer neural computation within textile platforms, woven or stacked fiber architectures can incorporate vertical (out-of-plane) interconnects formed via conductive-polymer junctions, nanometallic bridges, or ion-conducting vias, enabling genuinely three-dimensional neuromorphic mapping within mechanically compliant fabrics. This architectural strategy parallels recent advances in neuromorphic chip design, where energy-efficient communication across multiple neural layers is achieved through densely packed two-dimensional cross-bar arrays or vertically stacked three-dimensional memristive networks inspired by string-stacking approaches in 3D NAND flash memory [202, 203]. Translating these concepts to fiber-based systems requires circuit-efficient interlayer connectivity to support low-power, high-precision spike communication across stacked or woven neural layers [204, 205]. When integrated with memristive [40], ferroelectric [41, 42], or iontronic components [43, 44], such hierarchical fiber networks enable localized, programmable modulation of conductance states, supporting experience-dependent synaptic adaptation and distributed on-fiber learning. From a structural and usability perspective, textile-specific constraints, including flexibility, washability, mechanical durability, and user comfort, necessitate modular design strategies in which neural nodes and hidden layers can be embedded, interconnected, replaced, or reconfigured without compromising overall system integrity [33]. Advanced textile manufacturing techniques, such as Jacquard weaving, multilayer lamination, fiber-level interlocking, and connector-based modular architectures, provide viable pathways for implementing scalable, low-power, and reconfigurable multilayer neuromorphic fabrics [200, 206]. Ongoing efforts to refine fiber cross-sectional design, stabilize heterogeneous interfaces, suppress electrical and thermal crosstalk, and improve recyclability further position thermally drawn multifunctional fibers as a versatile and scalable neuromorphic hardware platform, capable of enabling future AI-driven intelligent materials and adaptive textile systems.

5.2 | Energy Efficiency and Adaptive Dynamics

A fundamental advantage of SNN-inspired computation is its inherently low energy footprint, arising from the sparse and event-driven activation of neurons, where spikes are generated only in response to salient input patterns [207]. This dynamic, temporally coded operation aligns naturally with the characteristics of energy-harvesting thermally drawn fiber platforms,

which can scavenge mechanical, thermal, or vibrational energy from their surroundings. From a structural and architectural standpoint, SNNs typically contain significantly fewer active neural nodes than conventional ANNs and inherently support synaptic pruning strategies to eliminate redundant pathways and reduce computational overhead. As illustrated in Figure 11, pruning selectively removes synaptic weights with negligible impact on inference performance, thereby achieving substantial model compression while preserving network functionality. Such pruning strategies, ranging from firing-rate-guided elimination [208] to STDP-based synapse quantization and periodic weight discretization [209], have been shown to reduce power consumption and accelerate computation, while maintaining high accuracy on benchmark tasks such as MNIST and Caltech-101. The distributed and fiberized embodiment of SNNs introduces an additional dimension of robustness. In a woven or multilayer fiber network, the ability to dynamically disconnect, reroute, or reconfigure fiber nodes parallels biological fault-tolerance mechanisms. A failure in one fiber segment can be compensated by adjacent fibers that reestablish conductive pathways or redistribute processing load, thereby maintaining global network performance. This adaptive resilience, together with the temporally encoded and sparsely activated dynamics inherent to SNNs, establishes a computational paradigm well suited for fiber-based neuromorphic systems operating under deformable, mechanically dynamic, and resource-constrained conditions. Such environments intrinsically entail significant uncertainty arising from mechanical perturbations, stochastic energy availability, and material-level variability [210].

5.3 | Toward Neuromorphic Smart Fiber Systems

Neuromorphic computation has traditionally been dominated by classical ML models such as SVMs and ANNs and their deep-learning derivatives, such as CNNs, RNNs, and DNNs (Figure 12a) [212]. These architectures, despite their algorithmic differences, share a reliance on dense, frame-based, synchronous processing executed through high-precision numerical operations [213]. Although modern training strategies and specialized hardware accelerators have improved their computational efficiency, they remain fundamentally limited by high throughput requirements, large memory footprints, and continuous data-sampling demands [180]. Such characteristics make ANNs poorly suited for environments that demand real-time inference, low-latency operation, and strict energy budgets, conditions typical of distributed or fiber-embedded sensing networks [214]. Besides, while SVMs operate through margin-based optimization rather than weighted nonlinear activations, they nonetheless exhibit the same dependence on centralized, synchronous computation [215], making them similarly unsuitable for energy-constrained, event-driven, or distributed environments. In contrast, SNNs, often identified as the third generation of neural networks, offer a fundamentally different computational paradigm. Instead of operating on continuous activations, SNNs encode information through discrete spike events whose timing carries semantic meaning [216]. This event-driven, asynchronous computation mirrors biological neural processing and supports sparse activity patterns, yielding orders-of-magnitude reductions in energy consumption compared to ANN-based inference [192]. These properties align directly with the requirements of fiber-based

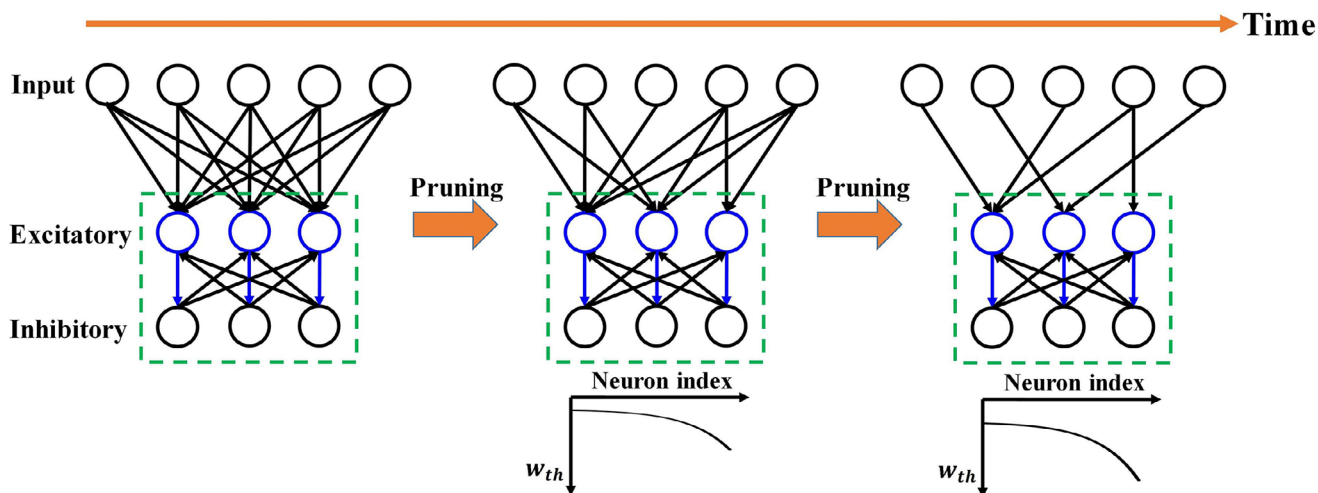


FIGURE 11 | Overview of the proposed pruning process, where synaptic pruning is progressively applied throughout training. Pruning is restricted to the synapses between the input and excitatory layers, as these are the only plastic connections whose weights are updated during learning. Reproduced with permission [211]. Copyright 2020, Frontiers Media SA.

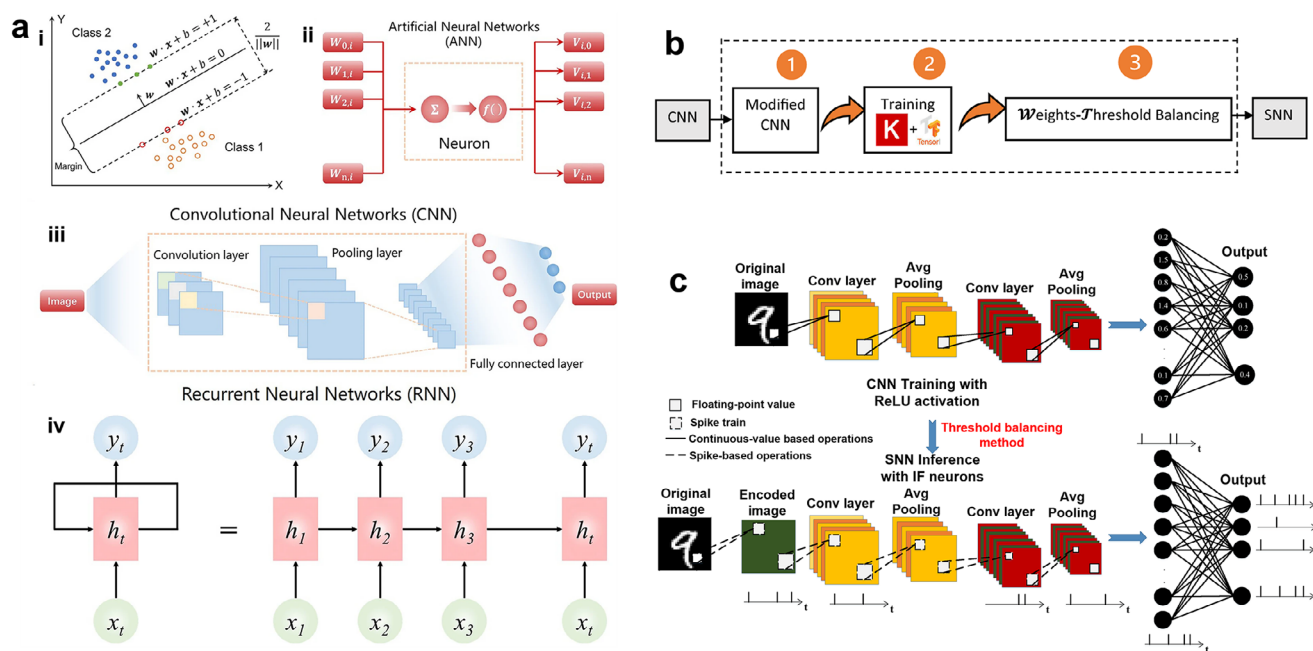


FIGURE 12 | Fundamentals of ML architectures and workflows for CNN-to-SNN conversion. (a) Overview of representative ML models: i) schematic of an SVM for binary classification; ii) ANN structure composed of weighted connections and nonlinear activation; iii) CNN architecture featuring convolution, pooling, and fully connected layers; iv) RNN architecture highlighting temporal sequence processing. Reproduced with permission [217]. Copyright 2024, Springer Nature. (b) General framework for mapping a trained CNN to a functionally equivalent SNN, involving three steps of network modification, training, and weights-threshold balancing. Reproduced with permission [212]. Copyright 2024, Springer Nature. (c) Illustration of the CNN-to-SNN conversion pipeline. A CNN is first trained using gradient descent with ReLU activations. An equivalent SNN is constructed by mirroring the CNN topology and transferring the trained weights. Layer-wise firing thresholds for spiking neurons are determined using an activation-based threshold balancing strategy, in which maximum CNN activations are used to normalize SNN thresholds. During inference, input images are encoded as spike trains and propagated through spiking convolutional layers and integrate-and-fire neurons for fully event-driven computation. Reproduced with permission [220]. Copyright 2022, MDPI.

systems, where sensing is distributed, power availability is limited, and computation must be performed locally along extended fiber architectures without reliance on centralized processors. When mapped onto fiber-based hardware, SNN-inspired circuits

could enable on-fiber event detection, context-dependent signal filtering, and closed-loop response, all powered by energy harvested through piezoelectric, triboelectric, or thermoelectric mechanisms. This stands in stark contrast to ANN-, RNNs- or

CNN-based approaches, which typically require off-fiber computation, extensive memory, and persistent sampling of redundant data streams. SNNs thus offer a pathway for developing fiber-scale neuromorphic primitives in which each fiber segment acts as a functional neuron or synapse capable of autonomous operation. Furthermore, SNNs are naturally compatible with event-driven sensor modalities, such as Single-Photon Avalanche Diode (SPAD) arrays and Dynamic Vision Sensors (DVSs) [180], which generate asynchronous spike-like events rather than continuous image frames. Unlike ANNs, which require expensive frame reconstruction and post-processing, SNNs can process event streams directly, enabling fully end-to-end neuromorphic pipelines suitable for compact, embedded, or textile-integrated devices [217]. This compatibility is particularly advantageous for thermally drawn multimaterial fiber systems incorporating photonically or electronically active fibers that inherently produce temporal, sparse, or threshold-triggered data.

A comparative analysis of major AI architectures relevant to fiber-based systems is summarized in Table 3. While ANNs, CNNs, and RNN/Transformers each exhibit strengths in specific data domains, their reliance on dense computation and centralized hardware limits their deployability within distributed fiber networks. In contrast, SNNs offer clear advantages for multimaterial fibers integration: ultra-low-power asynchronous processing, native suitability for event-based signals, and the ability to distribute computation across physically extended or woven fiber networks acting as local neurons and synapses. An emerging research trend focuses on converting trained CNNs into SNN analogues to merge the representational power of deep learning with the energy efficiency of spiking computation. As shown in Figure 12b,c, the process involves three main steps: (i) modifying the CNN architecture to make it spike-compatible, removing bias terms, replacing max pooling with average pooling, applying dropout for regularization, and substituting SoftMax with a spike-based output scheme; (ii) training the modified CNN using standard backpropagation; and (iii) transferring the learned weights to an equivalent SNN composed of integrate-and-fire neurons, followed by weight-threshold balancing to ensure accurate rate-based approximation of ReLU activations [212]. Proper threshold and weight normalization, typically achieved using data-driven scaling methods such as weight normalization [218] or the threshold balancing framework [219], is essential to prevent under- or over-firing of spiking neurons and to minimize accuracy loss during conversion. This conversion transfers learned CNN weights into an equivalent SNN architecture, followed by threshold balancing to preserve activation statistics. Input data are then encoded into spike trains for event-driven processing. This hybrid workflow, combining ANN training with SNN inference, has already demonstrated strong performance in image recognition and event-based vision tasks [220], and holds considerable promise for future thermally-drawn-fiber-based neuromorphic systems.

5.4 | Uncertainty Quantification for Robust Smart Thermally Drawn Fiber System

Uncertainty quantification plays a central role in the development of robust smart textile systems, spanning material selection, structural design, thermally drawn fiber manufac-

turing, sensing, and data-driven methodologies. Incorporating uncertainty quantification into AI pipelines yields several key benefits [221]. First, it enhances the robustness of forward predictions, particularly when data are limited or when distribution shifts occur, both common scenarios in multimaterial fiber systems. Second, uncertainty-aware AI can support inverse design tasks by quantifying confidence in proposed material or structural configurations. This allows for systematic exploration of design spaces and identification of configurations that are not only optimal but also reliable under realistic uncertainty conditions. Third, in deployed smart textile systems, modeling uncertainty improves sensing performance by enabling better discrimination between environmental noise and meaningful signals.

Across this full pipeline, and following the conventional uncertainty classification, the uncertainties can be categorized into two broad classes: aleatoric (data) uncertainty and epistemic (model) uncertainty [222–224]. Aleatoric uncertainty arises from intrinsic variability within the system, such as heterogeneity in multimaterial compositions, stochastic conditions during the manufacturing process, and imperfect real-world sensing [224, 225]. These uncertainties are irreducible and propagate across the material, fabrication, and sensing stages, influencing the reliability and robustness of downstream operations. For example, multimaterial fibers inherently contain microstructural variations along their length due to differences in constituent materials and the complexity of thermal drawing, and these variations can influence the macroscopic performance of sensing components integrated into textile systems [20, 226].

Manufacturing uncertainty is further compounded by external factors, including environmental disturbances, process-control errors, and thermal gradients. Because these factors act simultaneously and unpredictably, deterministic specifications often fall short of capturing the operational reality. Probabilistic methods therefore, provide a more meaningful perspective for decision-making under uncertainty, replacing fixed targets with probability-based performance metrics, reliability thresholds, and tail-risk considerations. Data-driven approaches such as model predictive control and deep reinforcement learning have emerged as promising tools for enhancing process robustness [116, 227]. These methods can incorporate stochastic variations directly into their control frameworks, supporting manufacturing strategies that remain stable despite fluctuations in operating conditions. Sensing uncertainty represents another significant challenge in the context of integrated fiber-based systems. Real-world deployment conditions introduce noise, environmental interference, and variations in physical stimuli [228, 229]. Probabilistic machine-learning techniques, including surrogate models for virtual sensing, have demonstrated the ability to jointly model sensor noise and physical variability [230]. This capability enables the propagation of uncertainty from raw sensor outputs to higher-level inferred quantities, improving reliability in downstream tasks such as classification, prediction, and control.

Epistemic uncertainty arises when AI models are used to interpret data or guide design and manufacturing, and, unlike aleatoric uncertainty, model uncertainty is reducible and reflects limited knowledge about model parameters or structures [230–232]. Traditional deterministic machine-learning models, trained

TABLE 3 | Comparison of AI models for emerging intelligent systems based on thermally drawn multimaterial fibers.

Category	Models	Core principle	Advantages/Disadvantages	Best-suited data type	Unique advantage for multimaterial fibers	Compatibility with multimaterial fibers
Classical ML models	ANN/DNN	Continuous activation; frame-based computation	Strong performance on large datasets, well-established tools/High computational load, large memory footprint, low interpretability.	Tabular, structured data	Centralized high-accuracy processing	Suitable for external processing; difficult to embed into distributed fiber networks
		KNN	Simple, adaptive, no training/Memory-intensive, slow inference at scale, noise-sensitive	Low- to medium-dimensional tabular data; feature vectors	Effective for small, localized datasets and calibration phases	Suitable for small datasets and edge-level processing; limited for fully distributed on-fiber inference
	SVM	Margin-based hyperplane optimization	Effective for high-dimensional and small datasets; robust/Sensitive to parameters, poor interpretability, synchronous computation.	Tabular, structured data	Lightweight inference; low-memory demand	Feasible for off-fiber preprocessing; limited suitability for dynamic on-fiber computation
Deep learning models	CNN	Spatial convolution; hierarchical feature extraction	Excellent for spatial sensing and image tasks/High sample demand; pooling causes info loss; computationally heavy.	Images, video, matrix-formatted data, spatial maps	Local feature extraction for imaging fibers	Useful for imaging fibers; not energy-efficient for on-fiber inference

(Continues)

TABLE 3 | (Continued)

Category	Models	Core principle	Advantages/Disadvantages	Best-suited data type	Unique advantage for multimaterial fibers	Compatibility with multimaterial fibers
Data preprocessing	RNN/Transformer	Temporal sequence modeling with recurrent or attention mechanisms	Strong for sequential/time-series data/Vanishing, exploding gradients; heavy computation; low efficiency.	Sequential data, time-series, speech, biosignals	Time-dependent representation	Hard to deploy in physical fiber systems due to computation & memory constraints
	SNN	Event-driven spiking; biologically realistic timing	Ultra-low power, sparse activation, asynchronous; ideal for event sensors/Training difficulty	Event-based, asynchronous signals	Distributed neuromorphic behavior resembling neurons/synapses	Ideal for distributed neuromorphic fiber systems enabling on-fiber learning
	PCA	Linear orthogonal projection maximizing variance	Noise reduction; efficient compression; low computational cost/Loss of fine-scale info; assumes linearity.	High-dimensional continuous sensor data	Enables low-power preprocessing before inference	Compatible with analog or neuromorphic preprocessing in fibers
	LDA	Supervised dimensionality reduction, maximizing class separability	Efficient low-power classification; robust for simple sensing tasks./Performs poorly for nonlinear data; risk of overfitting.	Labeled tabular or multichannel sensor data	Compact discriminative features for fiber-level classifiers	Highly compatible with lightweight on-fiber classifiers
	t-SNE	Nonlinear manifold learning preserving local neighborhood relationships	Excellent for visualizing complex multimodal data/High randomness, high computational cost; not suitable for real-time.	High-dimensional multimodal data	Useful during calibration and offline characterization	Only for offline analysis; incompatible with real-time fiber computing

via gradient-based or gradient-free optimization, produce point estimates that do not explicitly capture uncertainty. Bayesian AI models overcome this limitation by placing prior distributions over parameters and combining these priors with observed data through likelihood functions to yield posterior predictive distributions. These distributions naturally encode both prediction variability and model-based confidence.

Computing the posterior predictive distribution, however, is difficult for deep neural networks due to nonlinearities and high dimensionality. Gaussian process regression offers exact posterior estimation under restrictive assumptions but scales poorly with input dimension [233]. Bayesian neural networks (BNNs) address scalability but rely heavily on approximate inference strategies. A diverse set of such strategies has been developed, including Markov Chain Monte Carlo sampling, variational inference, Monte Carlo dropout, deep ensembles, and Laplace-based methods [234–236]. While these approaches provide practical approximations, they differ in computational cost, scalability, and fidelity to true Bayesian inference, limiting their usage for real-world problems with heteroscedastic data noise, when data noise is different with different design scheme or it varies in the sensing range. This problem has been tackled in applications of composites [237], yet, not been studied for thermally drawn fiber-based intelligent systems.

6 | Conclusions and Outlook

Multimaterial, multifunctional fibers fabricated via the thermal drawing process have evolved far beyond their original role in optical communication, emerging as a scalable materials platform capable of integrating sensing, actuation, memory, and computation within flexible, lightweight architectures. By harmonizing metals, polymers, semiconductors, dielectrics, ionic conductors, and active electronic materials within continuous microscale fibers, thermal drawing has established a uniquely versatile manufacturing paradigm for next-generation intelligent and adaptive systems. The integration of artificial intelligence into both the fabrication workflow and operational functionality of thermally drawn fibers marks a critical inflection point, transforming fibers from passive transduction elements into materials endowed with embedded perception, inference, and decision-making capabilities. At the manufacturing level, AI-assisted process control enables real-time optimization of drawing parameters, predictive defect mitigation, and data-driven preform design, thereby improving process device uniformity, stability, yield, and robustness in the presence of intrinsic material and process uncertainty. At the system level, fiber-integrated AI, implemented through embedded microcontrollers, neuromorphic circuits, or distributed inference nodes, supports in-fiber pattern recognition, multimodal signal fusion, and event-driven responses. Additionally, the incorporation of uncertainty quantification into these AI frameworks allows predictions to be accompanied by calibrated confidence estimates, enabling more reliable operation under real-world conditions characterized by noise, environmental variability, and limited data. Thereby enabling applications spanning wearable health monitoring, soft robotic actuation, human–machine interfaces, autonomous control, and distributed environmental sensing. We note that historically, the reliance on specialized fabrica-

tion machines has presented a potential barrier to the wider promotion and adoption of multimaterial fiber technologies. However, because the thermal drawing process was originally developed to manufacture silica optical fibers, drawing towers are already readily available in many conventional optical research institutions. Furthermore, establishing new facilities is becoming increasingly accessible, as the core requirements rely on well-established controls for temperature profiles, feeding and drawing speeds, alongside standard radius and force sensors. To further facilitate broader accessibility and democratize the manufacturing process, recent strategies have focused on the development of compact, bench-top drawing platforms, which have provided fibers with high quality. This accessibility is reflected in the rapid global adoption of the technology across both developed and developing nations, driven by its highly versatile applications in waveguides, robotic muscles, nerve-regenerating conduits, chemical sensors, and solar cells.

Parallel advances in neuromorphic computing further extend the functional scope of thermally drawn fiber systems by enabling artificial synaptic plasticity at the textile scale. Fiber-integrated resistive, capacitive, and memristive components have demonstrated hallmark synaptic behaviors such as potentiation, depression, and short-term memory. These developments lay the groundwork for learning-capable multimaterial fiber networks that support in-fiber memory formation, adaptive signal processing, and distributed decision-making analogous to biological neural tissues. Looking forward, several strategic research directions are expected to shape the evolution of AI-enabled thermally drawn fiber systems:

- Defining essential functional domains, including computation, sensing, communication, and power management, required for intelligent textile network architectures.
- Identifying neuromorphic elements suitable for fiber-based systems, such as artificial fiber neurons, synaptic junctions, and interconnected fiber neural networks.
- Exploring multilayered and woven neural architectures inspired by biological neural bundles to enable scalable, fabric-level SNN implementations.
- Developing spike-based encoding and classification schemes to realize event-driven processing and fiber-level learning frameworks.
- Advancing neuromorphic hardware design, including crossbar arrays, memristive fiber memory, and vertically integrated (2D/3D) fiber architectures for next-generation AI-enabled textiles.

These research directions are conceptually summarized in Figure 13, which illustrates how advances in materials science, device architecture, and machine intelligence collectively define the roadmap for next-generation AI-enabled textile systems. The emerging vision encompasses fabric-embedded AI algorithms, on-garment training and learning functionalities, and wearable memory elements capable of storing and updating model parameters in situ. Multilayered 2D/3D textile architectures and crossbar-array-based data-processing modules provide scalable pathways for high-throughput computation within woven structures.

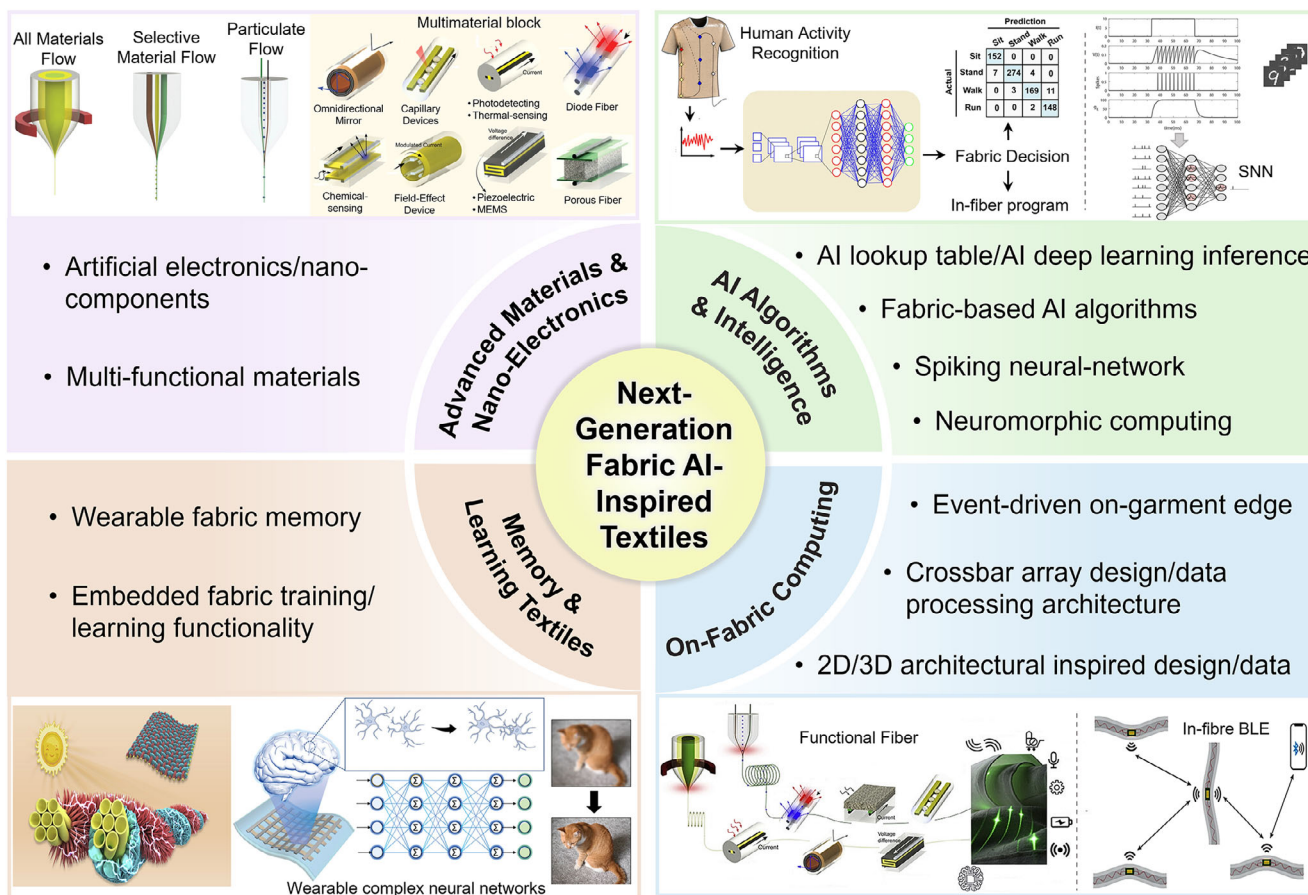


FIGURE 13 | Core components and emerging technologies driving the next generation of smart textiles. Reproduced with permission [47]. Copyright 2021, Springer Nature. Reproduced with permission [56]. Copyright 2020, Wiley-VCH. Reproduced with permission [130]. Copyright 2025, Springer Nature. Reproduced with permission [167]. Copyright 2023, Elsevier. Reproduced with permission [238]. Copyright 2020, Frontiers Media SA. Reproduced with permission [239]. Copyright 2024, Wiley-VCH. Reproduced with permission [240]. Copyright 2020, Elsevier.

In parallel, neuromorphic and spiking-neural-network-inspired fiber elements introduce event-driven, low-power computation that aligns with the constraints of distributed textile platforms. On-garment edge processors and artificial nano-electronic components further support real-time inference directly at the fabric level. These concepts outline a technological trajectory toward fabric AI systems in which sensing, memory, learning, and computation are woven seamlessly into textile form. These developments mark a transformative shift in textile science: from passive structural materials to active, high-performance platforms that integrate optical, electronic, piezoelectric, thermoelectric, triboelectric, and energy-storage functionalities. The maturation of AI-enabled multimaterial fibers is poised to deliver a new generation of intelligent, adaptive, and self-reconfiguring wearable technologies capable of reshaping human-machine interaction, pervasive sensing, and responsive material systems.

With the integration of AI, the thermal drawing process is increasingly being explored as a data-driven and adaptive manufacturing paradigm. Inspired by successful implementations of ML-assisted control in other continuous processes, such as polymer extrusion [241, 242], roll-to-roll manufacturing [243], and additive processing [244], recent studies have begun to demonstrate how ML algorithms can analyze real-time parameters, including temperature gradients, melt viscosity, and drawing tension, to

predict defects, manage uncertainty, enhance process stability, and enable adaptive optimization of operating conditions in fiber drawing systems [39]. Beyond process control, a key objective moving forward is to employ AI-driven materials discovery and structural optimization, through generative and reinforcement learning frameworks, to accelerate the identification of multimaterial fiber architectures tailored for advanced optical, thermoelectric, and biosensing functionalities. The maturation of AI-enabled thermally drawn multimaterial fibers is poised to underpin a new generation of self-aware, self-adaptive, and reconfigurable textile technologies, with profound implications for human-machine interaction, pervasive sensing, and responsive material platforms.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

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